Controller Refinement with Application to a Sugar Cane Crushing Mill

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Declaration

These doctoral studies were conducted with supervision from Professor Robert R. Bitmead of the Australian National University.

The work presented in this thesis is the result of original research carried out by myself, in collaboration with others, whilst enrolled in the Department of Systems Engineering as a candidate for the degree of Doctor of Philosophy. This work has not been submitted for any other degree or award in any other university or educational institution.

A significant proportion of the research performed for this thesis has been published, or has been submitted to conferences and journals as listed below.

Journal Papers

[J1] Partanen, A.G., R.D.Peirce and R.R.Bitmead (1994). Crushing Mill Control for Sugar Cane – a Robust, Nonadaptive LQG/LTR Strategy. *Control Engineering Practice*, Vol. 2, No. 1, pp. 3-16.

[J2] Partanen, A.G., and R.R.Bitmead. (1995). The Application of an Iterative Identification and Controller Design to a Sugar Cane Crushing Mill. *Accepted for publication in Automatica.*

[J3] Partanen, A.G. (1995). Advanced Control for a Sugar Cane Crushing Mill. *Submitted to the IEAust for publication.*

Conference Papers

[C1] Partanen, A.G., R.D.Peirce and R.R.Bitmead. (1993). Crushing Mill Control for Sugar Cane – a Robust, Nonadaptive Strategy, *Preprints, 12th IFAC World Congress*, Sydney, Australia, Vol. 4. pp. 407-410.

[C2] Partanen, A.G., and R.R.Bitmead. (1993). Excitation versus control issues in closed loop identification of plant models for a sugar cane crushing mill, *Preprints, 12th IFAC World Congress*, Sydney, Australia, Vol. 9, pp. 49-52.

[C3] Partanen, A.G., and R.R.Bitmead. (1993). Two Stage Iterative Identification / Controller Design and Direct Experimental Controller Refinement, *Proc. 32nd IEEE Conference on Decision and Control*, San Antonio, USA, pp. 2833-2838.

[C4] Bitmead, R.R., S.Crisafulli, C.R.Johnson Jr, and A.G.Partanen. (1994). Truth in

Modelling: Prejudices in Action, *Preprints 10th IFAC Symposium on System Identification*, Copenhagen, Denmark, Vol. 1, pp. 181-186.

[C5] Partanen, A.G., Z.Zang, R.R.Bitmead, and M.Gevers. (1994). Experimental Restricted Complexity Controller Design, *Preprints 10th IFAC Symposium on System Identification*, Copenhagen, Denmark, Vol. 2, pp. 177-182.

[C6] Partanen, A.G. (1995). Advanced Control for a Sugar Cane Crushing Mill. *Submitted to the IEAust CONTROL 95 conference*, Melbourne, Australia, October, 1995.

The work described in this thesis has been carried out in collaboration with a number of people. They are: R.R.Bitmead, S.Crisafulli, M.Gevers, C.R.Johnson Jr, R.D.Peirce, P.M.J.Van den Hof, and Z.Zang. However, the majority of the work is my own.

Ari Partanen,

Canberra,

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Acknowledgements

Despite having taken automatic control subjects during my undergraduate degree, my interest in feedback control systems was first aroused during my employment as an Electrical Engineer with Mount Isa Mines (MIM) Ltd. During this time, I was fortunate to work with Florido Bizzozero on numerous electrical engineering projects, including feedback control systems on the gigawatt thyristor converter drives that control the mine hoists at the Isa and Hilton mines. I became inspired by Florido's methodical manner. This led me gradually to heighten my own powers of observation and intellectual analysis and thereby to become successful at resolving many engineering problems, including those addressed in this dissertation. I am extremely grateful to Florido for the example he set when performing engineering tasks.

Following my escapades on mine hoists with MIM, I moved onto the control of sugar cane crushing mills at CSR Ltd's, Victoria Mill, Ingham. My current supervisor Professor Bob Bitmead was, at the time, and still is engaged as a process control control consultant to CSR Ltd. During my employment as process control engineer with CSR Ltd, Bob and I struck up a very effective working relationship which continues to this day. I would sincerely like to thank Bob for his patience and input on matters technical and non-technical.

Although, I left CSR Ltd to undertake a PhD, their sugar cane crushing process continued to dominate my research endeavours. I am indebted to the support I have received from CSR Ltd engineers, Rob Peirce, Matthew Ingegneri and Ted Seldon, of the Computer Services Department (CSD). In particular, I would like to make special mention of Rob Peirce's efforts in organising my many visits to tropical North Queenland during the 1993 and 1994 crushing season. The efforts of CSR Ltd Victoria Mill plant engineers, instrument fitters, and crushing station operators, too numerous to name individually, is gratefully acknowledged.

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Abstract

This thesis covers a broad range of theoretical and practical issues related to the application of controller refinement methods to the sugar cane crushing process with the ultimate aim of improving the extraction performance of this process.

Controller refinement relates to the adjustment of existing feedback controller parameters in an attempt to enhance closed loop process performance. The refinement of existing feedback controllers is the intent of fledgling iterative identification and control design schemes. The available iterative design methodologies are supported by and extend the mature fields of System Identification and Robust Control Design. The particular iterative design methodology which features in this thesis is the so-called *Zangscheme*. It consists of a model adjustment step followed by a controller enhancement step. In the model adjustment step, direct prediction error methods are used to perform closed loop identification, and in the controller enhancement step, a frequency weighted LQG control design is undertaken.

The profitability of a raw sugar factory is determined by the extraction performance of crushing units (mills) which make up a multi-stage milling train. In order to cope with the variations in the physical attributes of the incoming sugar cane and still achieve reasonable extraction at a prespecified throughput rate, feedback control of the sugar cane crushing process is essential. The extraction performance of this process is closely related to the torque exerted by the milling rollers. For the purposes of defining an appropriate control strategy, high extraction is equivalent to minimising torque deviations about a high torque set-point. In order to maintain throughput, at possibly the expense of extraction, the existing PID controllers operate with conservative process variable set-points. The need for tighter torque control of the sugar cane crushing process to ameloriate extraction motivates the application of controller refinement.

The sugar cane crushing process is a difficult-to-control process since an accurate dynamical model of the process and the disturbances acting upon it do not exist. Fortunately, approximate models which adequately describe the crushing process dynamics for the purpose of controller design can be identified. The difficulty in obtaining such models is compounded by the requirement that for safety and production reasons, the identification is performed with closed loop input-output data. High closed loop process performance is

also hindered by the occurrence and extent of the variations to the statistical properties of the process disturbance. Currently, it is not possible to predict these variations. Despite the vagaries associated with the crushing process, iterative identification and control designs schemes like the *Zangscheme* can be cajoled into delivering controllers which enhance closed loop process performance.

Successful application of the Zangscheme iterative identification and control design methodology to the sugar cane crushing process required an understanding of how the theoretical aspects of the iterative design are affected by process specific implementation issues. In acquiring this understanding, not only was theory of closed loop identification, frequency weighted LQG controller design, and iterative design, extended, but also a better comprehension of the crushing process behaviour was developed. In extending the theoretical issues, emphasis was placed on examining the role of operational and experimental closed loop input-output data in the controller design process.

For many industrial process, the sugar cane crushing process included, input-output process data is readily available. With the Zangscheme iterative design, operational data is not only employed to evaluate the performance of the current controller, it is also used to update this controller. Therefore the application of controller refinement to the sugar cane crushing process can be viewed as a logical extension of robust control ideas to accomodate *a posteriori* performance information.

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Chapter 1

Introduction

1.1 Thesis Motivation

The theoretical discourse presented in this thesis is aimed at the refinement of existing feedback control systems. The theoretical research issues examined have been motivated by the need to improve the performance of an extraction process in an Australian raw sugar production factory. In the author's opinion, with Research and Development (R&D) undertaken in a tax-payer funded university engineering department, the relevance of any theoretical endeavour would be incomplete without direct applicability to some industrial system.

Maximum sucrose extraction is one of the key objectives in maximising the profit of a raw sugar factory. The majority of sugar produced in Australia is sold on the world market and, as such, sugar prices are subject to the vagaries of cyclical price variations. In order to compete with those sugar producing countries which have low unit labour costs, sugar producers in developed countries like Australia (which have high unit labour costs) are heavily reliant on the benefits of advanced technology for their continued profitability.

The extraction of sugar-bearing juice trapped inside the cellular structure of the sugar cane plant is usually attempted with a milling train consisting of multiple crushing units. The primary objective of the crushing process is to maximise extraction at a reasonable throughput rate. Improved feedback control of the crushing process has been identified as an indirect mechanism by which to achieve higher extraction and a consequent improvement in the profitability of Australian raw sugar factory operations. Hence, the motivation for considering controller refinement in this thesis.

The refinement of existing feedback controllers is the intent of fledgling iterative identification and control designs. The available iterative schemes are supported by a solid theoretical framework associated with the mature fields of System Identification and Robust Control Design. As such, engineering insights provided in this thesis, which were critical to the development of a feedback control solution for the sugar cane crushing process, are sufficiently generic to have implications for potential application of these methods to other industrial processes.

The remainder of this brief introductory chapter includes a short discussion of research philosophy, a thesis overview, a listing of the original research contributions, and a statement of thesis significance.

1.2 Research Philosophy

The following definition epitomises the spirit in which the research described in this thesis was undertaken.

> *The task of research, and of the researcher, is to uncover what is hidden, to make transparent what is opaque and to reveal links, and meanings, where one might least suspect them.*
>
> Susan George
>
> The Debt Boomerang (1992), pp. 172.

The contribution of this engineering thesis is to make transparent what is opaque about certain theoretical aspects of iterative identification and control design with the view of successfully implementing this advanced technology in the Australian sugar industry. It is hoped that the insights provided are useful to the process control practitioner in realising successful advanced control[1] solutions using currently available design techniques.

It is the endeavour of the author to present the material in a manner which is accessible not only to academic researchers but also to engineers practicing process control who do not, necessarily, possess postgraduate qualifications. To what degree this mission has been accomplished will, ultimately, be determined by the individual readers.

[1] Advanced Control is defined as control above the Proportional-Integral-Derivative (PID) level.

1.3 Synopsis of the Thesis

Although, this thesis presents theoretical insights which have led to the gradual development of a multi-variable control solution for the sugar cane crushing process, the theory is sufficiently general so that it also applies to other multi-variable processes which can be adequately characterised by linear time-invariant finite-dimensional systems. The subjects dealt with include control design, identification, iterative design, and application to an industrial process. The problem statements and literature reviews are covered in the early chapters.

Chapter 2: Controller Refinement

Closed loop performance can be assessed using *a posteriori* operational and/or experimental information. If the performance does not meet design specifications then controller refinement becomes necessary. *A posteriori* information plays an important role in determining the manner in which the model identification and control design should be conducted in order to produce a controller which improves closed loop performance. A philosophical introduction to controller refinement is provided before controller refinement via successive model identification and control design is motivated. Thesis assumptions are also detailed and justified.

Chapter 3: Closed Loop Identification

Closed loop identification is an important component of iterative identification and control design. Direct and indirect methods of closed loop identification are investigated, with emphasis on their control-relevant nature and the design of experimental conditions.

Chapter 4: Iterative Identification and Control Design

Iterative identification and control design schemes enable progressive controller refinement. An overview of the currently available iterative identification and control designs is given. In particular, the so-called *Zangscheme* iterative design, the design methodology chosen for refining feedback controllers of the sugar cane crushing process, is introduced.

Chapter 5: Sugar Cane Crushing Problem

The nature of the sugar cane crushing problem is disclosed. The proposed control strategies are congruent with the process extraction objective. The adoption of an LQG controller design is justified. A natural extension to a single one-off LQG controller design is the

Zangscheme iterative identification and control design. Successful application of this technique has necessitated the resolution of a number of fundamental research issues. These research issues are stated in the chapter conclusion section of Chapter 5, since they are addressed in the subsequent two chapters.[2]

Chapter 6: Closed Loop Identification of Sugar Cane Crushing Process Models

The sugar cane crushing process effectively contains integrators. Therefore, stable operation of this production process for lengthy periods at reasonable throughput rates can only be achieved with feedback control. Consequently, identification of process models must be performed using closed loop input-output data. Successful application of the closed loop identification theory from Chapter 3 necessitates the selection of appropriate identification design variables. By taking into account *a priori* knowledge of the crushing process, the issue of appropriate design variable selection can be resolved.

Chapter 7: The Revised Zangscheme

The Zangscheme, an iterative identification and control design, uses weighted Least Squares identification and weighted LQG control design. Variant design procedures of the original Zangscheme are presented. The Zangscheme is extended to include cautious controller enhancement by making the frequency weightings for the controller design user scalable. A combination of both variants and cautious controller enhancement gives rise to a revised version of the original Zangscheme. The chapter finishes with a theoretical analysis which provides a better understanding of the manner in which frequency weightings used during the controller design affect the resultant closed loop performance.

Chapter 8: Application of Revised Zangscheme Iterative Design to the Sugar Cane Crushing Mill

The sugar cane crushing process has provided a rich proving ground for understanding the capabilities and the shortcomings of the modelling and control techniques considered. These techniques make heavy use of operational and experimental data to derive enhanced controllers. Comprehending the manner in which process characteristics influence the iterative design is the essential ingredient for the development of successful control

[2] This is one instance in which an application problem has been used to motivate research of a fundamental nature.

strategies. Various controller implementation issues related to the industrial environment were resolved prior to conducting online controller trails.

Chapter 9: Conclusions and Further Research

The thesis finishes with a conclusion chapter in which the major results are summarised, and avenues for possible areas for future research are stated.

1.4 Summary of Original Contributions

During the course of research and development for this doctoral dissertation, a number of original contributions have been made. These are the subject of journal and conference papers, as previously indicated. A brief description of the original work is listed below.

- **Closed Loop Identification Criterion [Section 3.3]:** The criterion for closed loop identification using direct prediction error methods is derived. The criterion is not entirely new, it has been stated in a less revealing form by Gunnarsson (1988) and in an incorrect form by Bitmead *et al* (1990). It also appears in Gevers (1993). Nevertheless, the criterion is fundamental and is used to promote a better understanding of the design issues surrounding closed loop identification. This is in itself a valid research endeavour, recall the definition of research from Section 1.2.

- **Selection of Closed Loop Identification Design Variables [Chapter 6]:** The selection of identification design variables is of great importance to the final outcome of the modelling process. To facilitate closed loop identification, an excitation signal needs to be added at the plant input. For the sugar cane crushing process, a thought experiment based upon *a priori* knowledge of process behaviour and closed loop identification theory systematically reveals the appropriate excitation signal to be injected during the identification experiment. Other identification design variables can be selected in a similar manner. *A priori* process knowledge also plays an important role in formulating model assessment checks.

- **Zangscheme Variants [Chapter 7]:** Two variants to the original Zangscheme have been proposed. With the first variant the model identification and controller design stages are partially decoupled. This modification better aligns the Zangscheme algorithm and should reduce the scope for controller misadjustment. The second variant is a direct controller design algorithm, therefore a process model identification is no longer required at every iteration.

- **Cautious Controller Enhancement [Chapter 7]:** Unlike other iterative design schemes, the original Zangscheme proceeds with not-so-cautious controller enhancement using frequency weighted LQG controller design. Caution can be built into the design criterion by scaling the effect of the frequency weightings.

- **The Revised Zangscheme [Chapter 7]:** A revised Zangscheme iterative design is proposed. By using a combination of the two Zangscheme variants, the revised Zangscheme features occasional model adjustment. It also features cautious controller enhancement through scalable frequency weightings. The revised Zangscheme is a practical iterative design methodology which has been successfully implemented on the sugar cane crushing process.

- **"Innovations" signals in Frequency Weighted LQG Controller Design [Chapter 7]:** A theoretical analysis of a closed loop system with an unknown plant and disturbance under the control of an LQG controller permits, for analysis, the isolation of a pseudo-innovations signal called the *predicted difference*. The predicted difference signal is the difference between the measured closed loop output and the output of the Kalman predictor component of the LQG feedback controller. If the unknown plant and disturbance correspond exactly with the plant and disturbance models used for the LQG controller design, the predicted difference signal would be white and equivalent to the Kalman predictor innovations process. However, given that the feedback controllers are usually designed using approximate estimates of the unknown plant and disturbance, the associated predicted difference signal will not be white. Nevertheless, by examining the whiteness of this predicted difference signal the suitability of a particular control design methodology or innovation can be interpretted. In this instance, it is the suitability of the Zangscheme frequency weighted LQG controller design which is under consideration.

- **Formulation of LQG Control Objectives for the Sugar Cane Crushing Process [Chapter 5]:** For the first time, model-based control was considered and successfully implemented for the sugar cane crushing control problem. A disturbance rejection LQG controller design was formulated for two different control criteria. To give the user the ability to manipulate sensibly the mathematical control design procedure in accordance with the demands of the process, *a priori* process knowledge featured in the selection of design variables. The first control criterion considered was based on accepted milling theory. The second control criterion evolved after it was found the controller designs using the first criterion did not secure the expected extraction improvements. Excogitation of the second criterion went against the traditionally-held view of sugar cane milling, and was therefore justified through careful process observation based upon open-loop step response tests, thought experiments, and process modelling. This exercise in itself contributed to a better understanding of process behaviour. LQG controllers which resulted in the minimisation of the second control criterion, given acceptable process models and appropriate design parameters, were found to be capable of delivering extraction benefits. However, to improve extraction performance, significantly, it became evident that resort to controller refinement techniques like the Zangscheme iterative design was necessary.

- **Application of the Revised Zangscheme to the Sugar Cane Crushing Mill [Chapter 8]:** Given a good understanding of the process, successful application of Zangscheme iterative identification and control design to the sugar cane crushing process was only achieved after adequately accommodating many practical issues in the theoretical development of a control refinement solution. These practical issues were a motivating force behind the development of the revised Zangscheme. Results from this application are valuable for setting a future research agenda.

1.5 Significance of the Research

The research contained in this tome deals with a broad range of theoretical and practical problems concerned with the use of experimentation, data analysis, identification, and control design in the engineering of control solutions. It treats a collection of important problems related to controller performance assessment and controller enhancement using operational data. This represent a logical extension of robust control design ideas to accommodate *a posteriori* performance information and makes a strong liasion between control design and identification. There exists an interplay between identification for robust control design and robust controller design or enhancement based on process data and identified models.

The entire tableau is not yet complete, especially from a theoretical perspective. However, many of the design issues have been exposed and empirical solutions have been found for the sugar mill application. This is a very active and exciting area of current research. Some of the many open problems are highlighted in the final chapter. The future development of theory, techniques, and tools[3] to facilitate the application of these methods should, hopefully, make advanced control more accessible to the practitioners. Ultimately, the practitioners will have the final judgement regarding this matter.

[3]Not to be confused with the more revealing definition of *tool* as applied by H.G.Nelson and rampaging Roy Slaven during radio broadcasts of "This Sporting Life" and more recently TV broadcasts of "Club Buggery".

Chapter 2

Controller Refinement

2.1 Chapter Motivation

Many industrial processes are often beset by marked variations in the grade of the incoming feedstock. This variability is of a stochastic nature and results in a large deviation of the process output from its desired set-point value. Poor process regulation usually has an adverse effect on the process objective. Improved rejection of the feedstock disturbance upon the process outputs can improve process performance and result in the recuperation of otherwise lost factory revenue.

Traditional PID (Proportional-Integral-Derivative) control covers the needs of many industrial processes (Nozaka, 1993). Multi-variable model-based controllers can be used to meet the demands of those processes where, either, PID control is not applicable, or where performance enhancement is sought. Performance enhancement may be required due to tighter process specifications, or simply due to poor performance with existing well-tuned PID controller. The use of advanced control techniques is not without considerable effort, often justified by economic benefits based upon anticipated performance enhancement (Richalet, 1993). In order for the material presented in this thesis to be of practical use, it is assumed that for a given process, the financial benefits have been quantified and that the anticipated returns justify the use of advanced control designs. It should be noted that quantifying the financial benefits is not a trivial exercise, often requiring long and expensive experiments.

Many industrial processes already operate under some form of feedback control, e.g. PID. Often economic and safety considerations dictate the presence of feedback controllers.

Therefore, it is natural to consider control design techniques which seek to refine the existing feedback controller(s) to enhance closed loop performance.

Traditional robust control techniques use models and model uncertainty assumptions. Readily available *a posteriori* closed loop process data from normal operation and experiments is not normally used by traditional robust control design methods to refine existing closed loop controller. The use of this *a posteriori* information to effect model adjustment and controller refinement to improve closed loop performance is emphasised heavily in this dissertation.

2.2 Theoretical Assumptions

Prior to exploring controller refinement, general assumptions which apply to the theoretical material advanced in this thesis, are now stated. Also, the relevance of the assumptions is justified. The first assumption is related to the nature of the closed loop signals. The second assumption applies to the process and disturbance transfer function descriptions.

The controller problem being considered in this thesis, disturbance rejection, treats the regulation of a process in the face of stochastic process disturbances. In some instances, the disturbance may also include a deterministic component, e.g. steps, pulses, ramps, sinusoids. In addition, the possibility exists for deterministic signals to be added to the plant and/or controller input. The technical machinery for model-based multi-variable controller design draws heavily upon the theory of stochastic processes (Doob, 1953), where the distinction between deterministic and stochastic signals can be de-emphasized if a quasi-stationarity assumption is used (Ljung, 1987).

Definition 2.2.1 *(Ljung, 1987). A stochastic process, $s(k)$, is quasi-stationary provided,*

$$\begin{aligned} Es(k) &= m_s(k), \qquad |m_s(k)| \leq C \quad \forall k, && (2.1)\\ Es(k)s(r) &= R_s(k,r) \qquad |R_s(k,r)| \leq C \quad \forall k, && (2.2)\\ \lim_{N\to\infty} & \frac{1}{N} \sum_{k=1}^{N} R_s(k,k-\tau) = R_s(\tau) \quad \forall \tau, && (2.3) \end{aligned}$$

The integer time index parameter k belongs to the index set, K, i.e. $k \in K, \quad k, K \in \mathcal{Z}$. E is the expectation operator with respect to the stochastic components of $s(k)$. N is the number of data samples in each of the individual realisation of a stochastic process.

Assumption 2.2.1 *All external signals are quasi-stationary.*

Remark 2.2.1 The integer nature of the index set implies that discrete time stochastic processes and consequently discrete time controller designs are under consideration in this thesis. Today, at least in the western world, most industrial processes are have been automated through the use of digital computer technology. For industrial processes with relatively slow dynamics like the sugar cane crushing process, the acquistion of process data on modern Distributed Control Systems (DCS) can be achieved at a necessary sampling rate of 4-10 times the process rise time (Åström and Wittenmark, 1990). As the sampling rate is sufficiently fast, yet not too fast, and as the controller will be implemented on a digital computer, continuous time controller designs need not be considered.

Remark 2.2.2 Bounds on the mean and auto-covariance in equations (2.1) and (2.2), respectively, imply that the stochastic process, $s(k)$, is well-behaved. In a practical application stochastic processeses are always bounded.

Remark 2.2.3 The third condition (2.3) implies that the covariance of a stochastic process can be determined from a single sufficiently long realisation. This is important, since the theoretical material for the design of a feedback controller often involves signal spectra. The power spectrum, Φ_s, of a stochastic process, $\{s(k)\}$, is the Fourier transform of its covariance function, R_s, i.e.

$$\Phi_s(\omega) = \frac{1}{2\pi} \sum_{\tau=-\infty}^{\tau=\infty} R_s(\tau) e^{-j\tau\omega}. \tag{2.4}$$

In practice, equations (2.3) and (2.4) provide a mechanism to compute an estimate of the covariance, and hence the signal spectrum, of a stochastic process from a finite length batch of signal data (Oppenheim and Schafer, 1975).

Remark 2.2.4 The restriction to quasi-stationary stochastic process implies that the theoretical methods considered will not apply to nonstationary processes.

The first step in the modelling of a system is to adopt an *idealisation* of the true system. With most industrial applications, perfect representations of complex systems are neither required nor are they constructible (Skelton, 1988).

Assumption 2.2.2 *The idealised plant, P, and the idealised disturbance, H, can be exactly represented by linear time-invariant finite dimensional (LTIFD) difference equations. However, the exact knowledge of the number and magnitude of the coefficients in these equations need not be known precisely.*

Remark 2.2.5 For many complex industrial processes, linearity assumptions allow a immediate and feasible controller design, albeit that the implemented controller is, at best, a crude approximation to an otherwise, often, unobtainable and unconstructible optimal controller.

Remark 2.2.6 A time-invariance assumption is often added, despite the fact that the process and/or the disturbance maybe time-varying. Difficulty in accurately characterising both the deterministic and stochastic nature of the time-variation for complex industrial processes has to some degree inhibited the use of time-varying controller design methods.

Remark 2.2.7 Controller implementation on the available factory computing environment necessitates a restricted dimensional design.

Remark 2.2.8 In keeping with the notation used in the literature, the system, (P, H), and its model, $(\hat{P}, \hat{H})$, shall be abbreviated to P and $\hat{P}$, respectively, where this does not bring confusion. In general, the terminology **system** will refer to the plant and disturbance pair, (P, H), whilst **system model estimates** refers to estimated plant and disturbance model pair, $(\hat{P}, \hat{H})$.

Approximate system model estimates can be obtained by :-

- physical modelling, where models are formulated using physical or chemical laws of nature.
- black-box modelling, where parametric models are fitted using only data collected during a model identification experiment on the process.
- grey-box modelling, where models are constructed using a combination of the above methods.

In this thesis, models used are, unless otherwise indicated, identified using black-box modelling techniques known as System Identification (Ljung, 1987). The focus is to use *a priori* process knowledge and *posteriori* data to manipulate black box modelling in a manner aligned with improving existing closed loop performance.

2.3 System Framework

The framework adopted in this thesis for considering linear time-invariant systems is that of Ljung (1987). Figure 2.1 shows the closed loop configuration under consideration in this thesis. The input-output relationships of the idealised LTIFD system of Figure 2.1 can be described as follows.

The output, $y(k)$, of the idealised plant, P, is given by

$$\mathcal{S}: \quad y(k) = P(z)u(k) + v(k), \tag{2.5}$$

where the plant input $u(k)$ is a quasi-stationary process with spectrum, $\Phi_u(\omega)$. $P(z)$ is a strictly proper rational transfer function. The argument, z, in $P(z)$ denotes the z-transform complex variable, while z in $P(z)u(k)$ denotes the shift operator, i.e. $z^n u(k) = u(k+n)$, $z^{-n}u(k) = u(k-n)$. The idealised disturbance, $v(k)$, which acts upon the process output, $y(k)$, is a quasi-stationary stochastic process described by,

$$v(k) = H(z)e(k), \tag{2.6}$$

where $e(k)$ is a sequence of independent random variables with zero mean values, covariances, σ_e, and bounded fourth moments. $H(z)$ is a proper rational stable transfer function of the form,

$$H(z) = \frac{C^d(z)}{D^d(z)}. \tag{2.7}$$

The polynomial $D^d(z)$ has all its zeros inside the unit circle. The polynomial $C^d(z)$ has zeros either inside or on the unit circle. Both polynomials are assumed to be monic. The spectrum of $v(k)$ is given by

$$\Phi_v(\omega) = \sigma_e |H(e^{j\omega})|^2, \qquad -\pi \le \omega < \pi, \tag{2.8}$$

where ω is the radian frequency. The plant input, $u(k)$, is determined by the control law

$$u(k) = r(k) - C(z)y(k), \tag{2.9}$$

where $C(z)$ is a LTIFD transfer function description of the feedback controller, and $r(k)$ is, either,

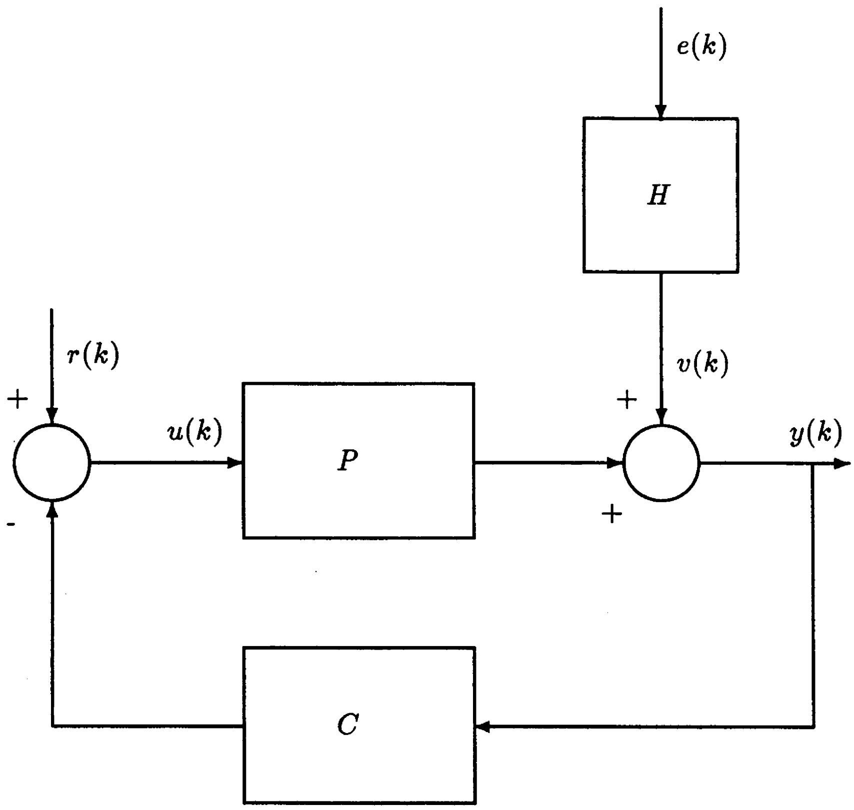

Figure 2.1: Achieved closed loop system.

- an excitation signal injected only during an identification experiment, or
- a reference signal for the controller to track.

Remark 2.3.1 The bounded fourth moment assumption on $e(k)$ allows the interchange of expectation and summation operators, necessary to derive computable formulae for the covariance and cross-covariance functions, $R_{yy}(\tau)$ and $R_{yu}(\tau)$, respectively (Åström and Wittenmark, 1990).

Remark 2.3.2 In general, in this dissertation the signal, $r(k)$, is an excitation signal as opposed to a reference signal, since disturbance rejection controller designs are under review.

Remark 2.3.3 Since second order statistics are used and $v(k)$ is bounded, $H(z)$, can be assumed to be both stable and stably invertible. That is, non-minimum phase behaviour in the disturbance cannot be identified from second order statistics. Hence, the cost-free restriction that C^d in (2.7) has its zeros on or inside the unit circle.

Remark 2.3.4 Equation (2.5) suggests that only a single, perhaps multi-variable, disturbance, $v(k)$, enters additively at the process output. It is assumed that process disturbances or noise entering at, either, the process input or within the process, have been lumped into the output disturbance, $v(k)$, (Ljung, 1987).

2.4 Performance Enhancement

The rapid development of computer controlled factory automation systems has resulted in a proliferation of process variable data exploitable for analysis. In particular, time domain input-output data associated with feedback control systems is readily available. An important aspect of advanced control for process industries concerns the financially justified use of time domain data to enhance the process performance through better feedback control systems design.

The refinement of a feedback controller relates to the adjustment of existing controller parameters in order to achieve improved closed loop performance. The subject of controller refinement considered in this thesis is formalised by the following definition.

Definition 2.4.1 Controller Refinement. *Controller refinement refers to the iterative process of the gradual enhancement of closed loop performance for an unknown, yet fixed, system, such that*

$$J^{ach}(P, C_{i+1}) \leq J^{ach}(P, C_i), \tag{2.10}$$

where the integer i refers to iteration index and J^{ach} is a criterion used to evaluate the closed loop performance achieved with the indicated controller. The lowest achievable closed loop performance is bounded below by the optimal performance, $J^{ach}(P, C^{opt}(P))$, where C^{opt} is the optimal admissible controller designed given exact knowledge of the system.

Remark 2.4.1 The performance criterion selected resolves the controller design method. Criterion selection is influenced by a combination of considerations related to :-

- the overall process objective. For example, the process objective for the hot-strip rolling process within the steel industry is to manufacture flat rolled steel to strict tolerances (Cheng *et al*, 1993). Regulation of the temperature profile of steel slabs leaving the reheat furnace plays an important role in determining the metallurgical properties of the final product. Therefore selected control performance criterion must be congruent with the overall process objective.

- the control design expertise of the user. Although some academic researchers may sit uncomfortably with this unscientific notion, and in some extreme cases even refuse to accept that it does exist, it is nevertheless is a fact of life that the user's level of comfort dictates the application of certain design techniques over others. Performance criterion selection based on this pragmatic insight can be justified by the availability of user software specific to a particular design method, and end-user requirements regarding delivery time of a control solution.

Remark 2.4.2 Controller refinement is initiated when the controller performance on the true system is recognised as not meeting the design specifications. Controller refinement can be considered as the supervised retuning of an existing feedback controller. Similarly, with commercial PID single-loop controller products that incorporate auto-tuning, the user recognises the need for controller retuning and then initiates and supervises the automatic refinement of an online controller (Åström *et al*, 1993).

2.5 Robust Adaptive Control

The following heuristic arguments for placing controller refinement into robust adaptive control context were used by Lee, (1994), and Schrama (1992a).

For uncertain systems, the criteria for controller design and closed loop performance evaluation depend upon different quantities. The design criterion depends upon the model estimate of the system, whilst the evaluation criterion involves the uncertain system. The approach of robust control design attempts to account for an *a priori* specified worst-case discrepancy between uncertain system and its estimate (Green and Limebeer, 1995, Doyle *et al*, 1992, Maciejowski, 1989, Morari and Zafiriou, 1989, Doyle and Stein, 1981). Therefore, a robust controller is one designed on the basis of *a priori* information (Zames and Wang, 1992). An adaptive controller makes use of *a posteriori* information to achieve better performance than could be obtained with an initial robust controller (Zames and Wang, 1992).

Assumption 2.5.1 *It assumed that the existing feedback controller can classified as a robust controller in the sense of Zames and Wang (1992).*

Remark 2.5.1 Practically all controllers are designed on the basis of some *a priori* knowledge and therefore, in the sense of Zames and Wang (1992), can be considered to be robust.

If the closed loop performance of an initial robust controller meets design specifications, an adaptive design is not required. However, if the design specifications are not meet, resort to an adaptive design is warranted. With traditional adaptive control (Åström and Wittenmark, 1989, Gupta, 1986, Goodwin and Sin, 1984), the adjustment of the existing controller parameters occurs continually as new data is logged, in other words on-line. With controller refinement as considered in this volume, a batch of recently collected closed loop input-output data is used to make off-line adjustments to the existing controller. Only after the adjustments are completed is the enhanced controller ready for feedback control. Since off-line controller refinement also uses *a posteriori* data it can also be considered to be an adaptive control design method.

By definition, controller refinement would not be necessary if the current robust controller achieved closed loop performance specifications. Therefore, controller refinement includes both a robust and adaptive agenda and the associated technical issues are those of **robust adaptive control**. This is confirmed in Schrama and Bosgra (1993), Lee *et al* (1993a), who combine adaptation and robust control through an iterative identification and control design for controller refinement.

With controller refinement for uncertain systems, the design of an enhanced controller according to a particular design criterion depends upon the current closed loop system, system estimates, a model uncertainty description, and certain design variables available for user manipulation.

Definition 2.5.1 Controller Design. *The design of an enhanced feedback controller for the unknown system, P, is the search for a controller, C_{i+1}, in some class, $\mathcal{C}$, which minimises a design criterion, J^{des}, for a specific system model estimate, $\hat{P}_{i+1}$, i.e.*

$$C_{i+1} = \arg\min_{C \in \mathcal{C}} J^{des}(\hat{P}_{i+1}, C, \Delta_{i+1}, \chi_{1,i+1}), \tag{2.11}$$

where

$$\hat{P}_{i+1} = f(P, C_i, \chi_{2,i+1}). \tag{2.12}$$

Δ refers to a linear time-invariant (LTI) stable plant perturbation, χ_1 to a set of control design variables, and χ_2 to a set of design variables which influences the modelling outcome.

Remark 2.5.2 Definition 2.5.1 concedes that the model-based controller design is dependent upon a previous model identification step. That is, the modelling and control design processes are iterative in nature (Schrama, 1992b, Skelton, 1988). The emergent field of iterative identification and control design schemes presents systematic and theoretically justified procedures to achieve performance enhancement (Van den Hof and Schrama, 1994, Gevers, 1993).

Remark 2.5.3 The inclusion of design variable sets allows the user to influence the outcome of a mathematical design procedure. Therefore, the issue of design variable selection is of great importance. In this thesis, aspects of design variable selection for both the model identification and controller design are examined.

Remark 2.5.4 The unconstrained minimisation given in Definition 2.5.1 does not guarantee performance enhancement. Unfortunately, constraining the minimisation subject to,

$$J^{ach}(P, C_{i+1}) \leq J^{ach}(P, C_i),$$

leads to a mathematically intractable problem since the system, P, is unknown.

Remark 2.5.5 In a standard "certainty equivalance" LQG controller design, the plant perturbation, Δ, is zero, whereas with H_∞ control designs Δ is typically non-zero. Therefore, in the case of a H_∞ control design an estimate of the plant pertubation, which defines an uncertainty set associated with a particular plant model, is required.

2.6 Uncertainty Sets

Uncertainty sets define a bound on the mismatch between the plant and its nominal model. Kosut (1995) considers uncertainty sets as a collection of unfalsified models. That is, all possible member plant models within the uncertainty set can, in some sense, adequately reflect the dynamical behaviour captured by a given input-output data set. With robust control design methods, the structure and size of the dynamical perturbation is used to define an uncertainty set.

Definition 2.6.1 *(Van den Hof and Schrama, 1994) An uncertainty set, $\mathcal{P}_\Delta(\hat{P}, b)$, restricted in size by a scalar metric, b, induced by the nominal plant model, $\hat{P}$, and an uncertainty structure, Δ, is defined as*

$$\mathcal{P}_\Delta(\hat{P}, b) \triangleq \{P^* \quad s.t. \quad |P^*(e^{j\omega}) - \hat{P}(e^{j\omega})|g(e^{j\omega})^{-1} \leq b\} \quad -\pi \leq \omega < \pi, \tag{2.13}$$

where g is some real-valued weighting function.

Remark 2.6.1 Definition 2.6.1 is a general definition for unstructured uncertainties, that is, an uncertainty about which no information is available except for an upper bound on the magnitude of its frequency response. Structured uncertainties are also possible (Green and Limebeer, 1995, Doyle *et al*, 1992, Maciejowski, 1989, Morari and Zafiriou, 1989). However, for many complex industrial processes it is difficult to characterise reliably the unstructured uncertainty estimates, let alone the more specific structured uncertainty estimates.

Remark 2.6.2 Typically, available robust control designs incorporate disturbance model uncertainty by specifying an *a priori* norm bound on the disturbance signal, rather than probabilistic models of the disturbance process and the associated disturbance model mismatch (Mäkilä *et al*, 1994). Bounded disturbance signals are used in set membership identification (Milanese and Vicino, 1991, Norton, 1987, Fogel and Huang, 1982)

Remark 2.6.3 Given an uncertainty set, $\mathcal{P}_\Delta(\hat{P}, b)$, the robust control design problem is to construct a controller, $C(\hat{P}, \mathcal{P}_\Delta(\hat{P}, b))$, which achieves certain specifications for all plant models in the uncertainty set. This is the philosophy of a worst-case design.

Remark 2.6.4 Worst-case bounds on the uncertainty set can be estimated from finite length closed loop input-output data sequences (Hakvoort, 1994, Hakvoort and Van den Hof, 1994, de Vries, 1994, Kosut *et al*, 1992, Kosut, 1988). Similar approaches limited to open-loop data include those of Goodwin *et al*, 1992, Wahlberg and Ljung, 1992.

Remark 2.6.5 As has been pointed out in Section 2.2 many industrial processes, the sugar cane crushing process included, can only be crudely approximated by linear time-invariant systems. Given an algorithm which produces an estimate of the worst-case bound, a methodology to validate the estimate is required before it can confidently be used in any robust control design. To the author at least, it is unclear whether algorithms developed for the purposes of model uncertainty estimation include a validation procedure. For example, does there exist a simple sensibility check for validating the order of magnitude of the estimated bound. In the early 1990s, the lack of model uncertainty estimation algorithms, and just as importantly, reliable software to implement these algorithms, mitigated against the use of robust control design methods which required model uncertainty estimation for the sugar cane crushing problem. Nevertheless, the concept of uncertainty set is fundamental to understanding controller design for unknown systems.

The ultimate aim of controller refinement is high performance control. In order to design a feedback controller which achieves high closed loop performance for an uncertain system, the size and structure of the uncertainty set needs to be limited (Van den Hof and Schrama, 1994). This observation asserts that with a robust control design the achievable closed loop performance is a reflection of the uncertainty set size and hence confidence in the model estimates. In order to gain performance improvement, controller refinement requires an investigative agenda to reduce the size of the uncertainty set associated with a particular plant model. Such an agenda is the realm of a stochastic adaptive control philosophy known as **dual control** (Fel'dbaum, 1965, Wittenmark, 1975).

2.7 Probing and Caution in Stochastic Adaptive Control

The concept of dual control was introduced by Fel'dbaum (1960-61) for systems for which the parameters are not known precisely. Fel'dbaum recognised that control signals should not only seek to direct the process, but should also probe with the view to obtaining information. Hence, the control signal is said to possess a reciprocal or *dual* nature.

Definition 2.7.1 *(Åström and Wittenmark, 1989). Dual control is the property of an optimal controller which achieves the correct balance between maintaining small control signals and parameter estimation errors for a given performance criterion.*

For a given control criterion, a dual controller during each sample interval computes the optimal control value for the next sample instance using dynamic programming (Bellman, 1957). The dynamic programming algorithm requires past input-output process variable measurements and *a priori* specified probability distributions for the plant and disturbance parameters.

Remark 2.7.1 For linear systems with possibly time-varying parameters, dual control solutions have been formulated for minimum variance criteria (Åström and Wittenmark, 1971), and Linear Quadratic criteria (Tse and Bar-Shalom, 1973). With the exception of single-step versions of these criteria, minimising solutions which are analytic are not available. Only in simple cases is a numerical solution for the multi-step criteria practical (Åström and Wittenmark, 1989).

For systems which could be accurately described by the identified model estimates, the recent results of Kulcsár (1995) as quoted by Gevers (1995), confirm that even a suboptimal dual control law is superior to the so-called certainty equivalence approach inherent in model-based controller designs. Unlike dual control, certainty equivalence controller designs assume that estimated model parameters are exact, i.e. the model parameters have zero uncertainty. This assumption dramatically simplifies the design procedure, hence currently certainty equivalence control design are the norm.

Unfortunately, even sub-optimal dual control methods are difficult to implement from a practical perspective. However, the dual control concept possesses some attractive features which are prominent, albeit in a partial or embryonic manner, in several certainty equivalence iterative approaches to controller refinement (Gevers, 1993). The attractive features of dual control are,

- a cautious controller design in which model parameter uncertainty is taken into account, and
- active learning of the system parameters by including an investigative agenda to the control law.

Definition 2.7.2 *(Jacobs and Patchell, 1972). A controller is said to be cautious, if its gain is determined according to the accuracy of the estimated system parameters.*

Remark 2.7.2 Large uncertainty in the parameter estimate typically implies caution through a low gain controller. Since certainty equivalence controllers do not make any allowance for model parameter uncertainty, such controllers are not considered to be cautious. However, by appropriately formulating a certainty equivalence control design, the consequent adjustment of an existing controller can be considered to cautious, even though the updated controller cannot be considered to cautious in the sense of Definition 2.7.2.

Definition 2.7.3 *Active learning refers to the process of deliberately probing the unknown system in order to obtain accurate parameter estimates.*

Remark 2.7.3 A dual control automatically includes an investigative component. However, with a sub-optimal dual control, this investigative agendum may vanish. Nevertheless, active learning can still be introduced into sub-optimal dual control by injecting excitation signals at the plant input (Jacobs and Patchell, 1972, Wieslander and Wittenmark, 1971). The same applies for certainty equivalence control design.

Gradual controller refinement through iterative identification and controller design is akin to dual control except that cautious controller enhancement is performed instead of cautious controller design, and active learning is promoted by the deliberate injection of excitation signals rather than through a control law which naturally includes an investigate component. With the iterative controller design schemes, cautious controller enhancement can be imposed by restricting the magnitude of controller adjustment possible during the controller design, whilst active learning is promoted through the use of excitation signals during closed loop identification experiments.

Remark 2.7.4 (Anderson *et al* (1994). Under reasonable conditons, small perturbations to an existing achieved closed loop stabilising controller, as measured by an H_2 or an H_∞ norm of a Youla-parameter, should result in a small adjustment to the existing controller parameters. The Youla-parametrization defines a set of all stabilising controllers for a given plant model (Youla, 1976a, 1976b). In the case of LQG type controllers, the resultant change in closed loop performance with the perturbed controller operating on the true plant will be small provided the plant/model perturbation is small. Cautious controller refinement through iterative identification and control design implicitly relies upon this assumption, that a small change in the plant parameters should result in a small change in the controller, and hence a small change to the achieved closed loop system.

2.8 Iterative Design

Iterative identification and control have resulted from recognising the interplay between modelling and control designs (Van den Hof and Schrama, 1994, Gevers, 1993). Åström and Wittenmark (1971) combined identification and control design in a dual control law and demonstrated that the achieved performance was superior to that which was obtained with separate identification and control designs. As mentioned in Section 2.7, practical difficulties with the combined approach typically result in an intractable solution, hence separate identification and control design are still the norm. Nevertheless, it has been recognised that if separate algorithms for identification and control design are to used, then these algorithms should be used in an iterative manner (Schrama, 1992b, Skelton 1988).

Gevers and Ljung (1986) showed that an optimal restricted complexity model for minimum variance control design, resulted from an identification performed using experimental input-output data collected whilst the system is operating under feedback control. In this context, closed loop experimental conditions for identification were beneficial to control. Furthermore, for various control criteria, minimum variance, LQG, and model reference, Hjalmarsson *et al* (1994a), show that identification of full-order plant models from closed loop data gives a controller with better closed loop performance than that which would have resulted from a model fitted using open-loop data. These results lend further support for conducting controller refinement through an iterative scheme with successive stages of closed loop identification and control design.

Remark 2.8.1 Although, the results of Hjalmarsson *et al* (1994a), Gevers and Ljung (1986), indicate that closed loop identification of plant models for control design is beneficial, it is by no means necessary. Ljung (1993) points out that given a good disturbance model it is immaterial whether the plant input is generated in open or closed loop, provided that it has a certain spectrum. Furthermore, the appropriate input spectrum may be naturally generated in closed loop identification. This, as Ljung (1993) correctly observes, justifies, as opposed to necessitates, the use of closed loop identification.

Remark 2.8.2 Mäkilä *et al* (1994) argue that the lack of hard-results, as opposed to heuristics, does not support the alleged advantages of successive closed loop identification and controller design. Certainly, in some instances, the restricted complexity controllers obtained by identification from either, open or closed loop, input-output data may not always be the "best" controller (de Bruyne and Gevers, 1994). On other occassions, the iterative schemes may diverge when the design specifications are unreasonable (Åström and Nilsson, 1994). Nevertheless, iterative design methods, like many other control design methods, can be cajoled into achieving performance enhancement for factory-scale industrial processes (Partanen and Bitmead, 1995). Indeed, it is the aim of this dissertation to explain and demonstrate the connection between iterative design and process understanding which adds weight to these methods. There is an absence of hard results of immediate applicability to industrial systems with other approaches as well. This is the motivation for this research.

Remark 2.8.3 Unlike traditional adaptive control methods, iterative identification and control design methods optimise the model parameters according to an identification criterion given a fixed controller, then the controller parameters are optimised according to a control criterion given fixed model parameters. With traditional adaptive control methods, model and controller parameters are continually adjusted at every sample instance. That is, the model and controller parameters are fixed for only one sample interval. Hence, iterative identification and control design can be considered as a slowly adaptive control method (Bitmead, 1993), or as self-tuning with infrequent controller updates (Åström and Nilsson, 1994). This observation provides further support for the connection between iterative design and robust adaptive control elucidated in Section 2.5.

The general structure of the available iterative design schemes, in which separate stages of identification and control design are performed, is now motivated. This can be done by considering a pair of triangle inequalities which bound the achievable control performance (Van den Hof and Schrama, 1994).

Proposition 2.8.1 *Assuming that no idealisation is required, i.e. the unknown system corresponds to a LTIFD system, the achievable performance on the unknown system with the enhanced controller, C_{i+1}, is bounded above and below by the following triangle inequalities for performance norms (Van den Hof and Schrama 1994, Schrama, 1992a) :-*

$$J^{ach}(P, C_{i+1}) \leq J^{des}(\hat{P}_{i+1}, C_{i+1}) + J^{pd}(P, \hat{P}_{i+1}, C_{i+1}), \tag{2.14}$$

$$J^{ach}(P, C_{i+1}) \geq |J^{des}(\hat{P}_{i+1}, C_{i+1}) - J^{pd}(P, \hat{P}_{i+1}, C_{i+1})|, \tag{2.15}$$

where

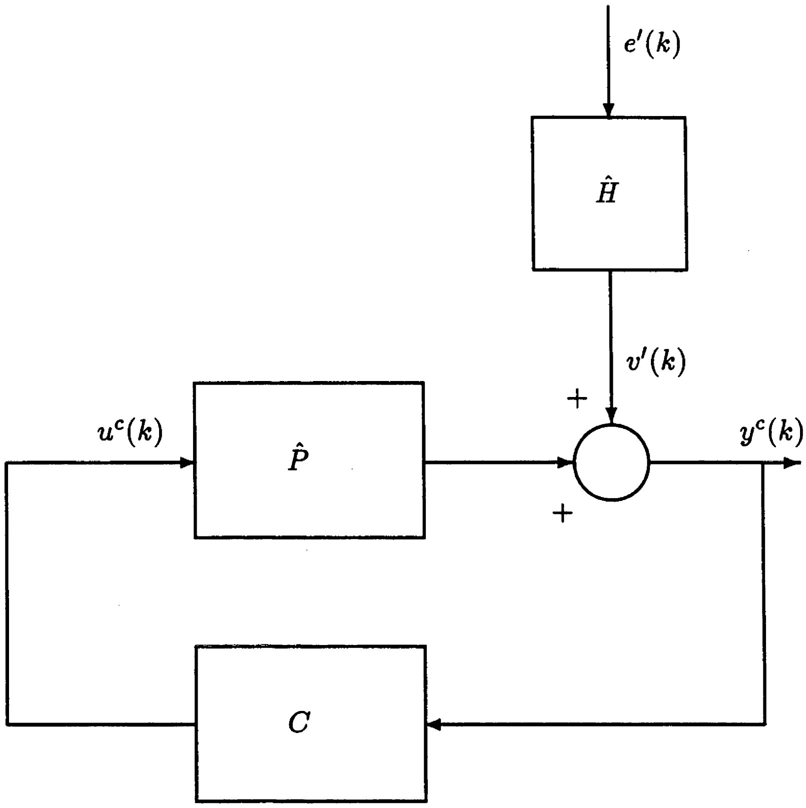

Figure 2.2: Designed closed loop system.

- J^{ach} *is the control performance achieved on the unknown system shown in Figure 2.1.* J^{ach} *is termed the* **achieved performance.**

- J^{des} *is the control performance designed using the system model estimate approximation of the unknown system. The closed loop system used in the controller design is shown in Figure 2.2.* J^{des} *is known as the* **nominal** *or* **designed performance.**

- J^{pd} *is the degradation in designed performance associated with the fact that the enhanced controller,* C_{i+1}*, has been designed using the model estimate,* $\hat{P}_{i+1}(\theta)$*, rather than the unknown system,* P*, i.e.*

$$J^{pd}(P, \hat{P}_{i+1}, C_{i+1}) \triangleq |J^{ach}(P, C_{i+1}) - J^{des}(\hat{P}_{i+1}, C_{i+1})| \tag{2.16}$$

J^{pd} *is usually referred to as the* **performance degradation.**

Since the true plant and disturbance are unknown, it is not possible with a model-based approach to controller refinement to minimise directly the achieved performance, J^{ach}. Nor is yet possible to optimise directly the right-hand side of the triangle inequalities, (2.14) and (2.15). As will be soon detailed, available iterative identification and control design techniques can be used to minimise indirectly the achieved performance, J^{ach}, by addressing the minimisation of the individual performance norms on the right-hand side of the triangle inequalities, (2.14) and (2.15).

Remark 2.8.4 Direct minimisation of the achieved performance, J^{ach}, is possible with the non-model-based iterative scheme of Hjalmarsson *et al* (1995, 1994b, 1994c). This approach does not require a model of the process nor the disturbance. Experimental closed loop input-output data and knowledge of the current controller is used to update the current controller parameters in such a manner as to minimise gradually the achieved performance. Although the scheme is locally convergent, cautious controller enhancement is still warranted since the experimental data depends upon the unknown disturbance process. The model-based iterative approaches are equivalent to this direct scheme, when the achieved closed loop sensitivity matches the design sensitivity, that is, if the identified plant model matches true plant for a given controller. Currently, the iterative scheme of Hjalmarsson *et al* (1995, 1994b, 1994c), applies only to single-input single-output (SISO) systems. However, a multi-variable version is expected. This direct iterative design scheme was successfully trialled on the sugar cane crushing process, refer Section 8.3.1. Unfortunately in this instance, its ultimate usefulness was limited through the lack of a multi-variable design version.

Remark 2.8.5 The various performance norms, J^{ach}, J^{des}, J^{pd} correspond with particular identification or control criteria. These norms will be bounded if the closed loop system is stable.

Remark 2.8.6 Gevers (1993) refers to J^{pd} as a performance robustness measure.

Iterative identification and control design is a procedure for the indirect minimisation of the achieved performance, J^{ach}. By using available design methods of identification and control design, the individual quantities on the right-hand side of the triangle inequalities, (2.14) and (2.15) can be minimised. The manner in which the individual identification and control design are conducted needs to be coordinated in order to attain high achieved control performance (Bitmead *et al*, 1990). The requirements for high achieved control performance are (Van den Hof and Schrama, 1994, Schrama, 1992a),

1. high designed or nominal performance, i.e. J^{des} small.

2. a performance degradation much smaller than the designed performance, i.e. $J^{pd} << J^{des}$.

Both requirements are those of a robust control design paradigm. In practice, the first requirement is secured through a controller design as per Definition 2.5.1, i.e.

$$C_{i+1} = \arg\min_{C \in \mathcal{C}} J^{des}(\hat{P}_{i+1}, C, \Delta_{i+1}, \chi_{1,i+1}), \tag{2.11}$$

The second requirement is more problematic. Unfortunately, high nominal performance and robustness are sometimes conflicting requirements, i.e. attempting to make J^{des} too small may have a detrimental impact upon J^{pd}, for a given $(P, \hat{P}, C)$, causing a degradation rather than an enhancement of closed loop performance (Schrama, 1992a, McFarlane and Glover, 1988). In order, to improve the compatibility of a plant model for both high nominal control performance and robustness, the minimisation of J^{pd} can also be undertaken by performing model identification using closed loop data collected with the current controller, C_i, operating, i.e.

$$\hat{P}_{i+1}(\theta) = \arg\min_{\theta} J^{pd}(P, \hat{P}(\theta), C_i, \chi_2), \tag{2.17}$$

where θ is the parameter vector associated with the parametrized model estimate, $\hat{P}$. This minimisation is slightly different from that desired, since it necessarily involves the currently available controller, C_i, as opposed to a future controller, C_{i+1}, which depends upon the result of this optimisation.

The identification of plant models according to a control-oriented criterion, such as J^{pd}, is classified as a **control-relevant** identification (Gevers 1995, Zang *et al*, 1995, de Callafon *et al*, 1994, Hakvoort *et al*, 1994, Van den Hof and Schrama, 1994, Gevers, 1993, Lee *et al*, 1993, 1992, Åström, 1993, Rivera *et al*, 1992, Rivera, 1991, Rivera *et al* 1990, Schrama, 1991a, 1991b, Bitmead *et al*, 1990, Hansen, 1989, Hansen *et al*, 1989, Gevers and Ljung, 1986). The extent of research effort in this direction is indicative of the importance of using models which are tailored for control purposes in order to achieve high performance. Control-relevant plant models, in general need to be accurate in the vicinity of the cross-over frequency of the closed loop system. Closed loop identification automatically amplifies model errors around this frequency and therefore is predisposed to yield a control-relevant model. High model accuracy in the neighbourhood of the eventual cross-over frequency is crucial for the enhancement of control performance in a subsequent control design.

Remark 2.8.7 Many process industry organisations attempt to develop *gargantuan* models of process behaviour. Such models may play an important role in process understanding, process design, simulation, operator training, etc. However they are unlikely, in their gargantuan form, to be suitable for a restricted complexity controller design. In the case of restricted complexity controller designs for uncertain systems, it is well known that a nominal plant model used in the design of controller which delivers high closed loop performance, may not necessarily be good open-loop predictor (Schrama, 1992a, Gevers and Ljung, 1986, Åström and Wittenmark, 1973). That is, there is a penalty associated with the use of models with many parameters. The observation is encompassed in the principle of parsimony (Söderström and Stoica, 1989, Ljung and Söderström, 1983). With controller design, the model is a vehicle for high performance controller design, and does not necessarily need to be an accurate representation of process behaviour (Gevers, 1993). The intended application of a particular model should determine the required model characteristics.

Remark 2.8.8 Process control practitioners, be they tradespersons or engineers, are heavily reliant upon process observations and rule-of-thumb adjustments to tune most industrial feedback controllers. For example, with the well-known Zeigler-Nichols tuning rules for PID controllers (Stephanopoulus, 1984), adjustments to the proportional, integral, and derivative gains are based upon observing the closed loop response of the process output to input step or pulse transients, i.e. closed loop experiments are performed. Necessarily, the tuning process is an iterative one. With such rule-of-thumb tuning algorithms, the final controller gains are attained by monitoring the behaviour of process input-output signals and making the approriate controller gain adjustments. It is in this respect, that the rule-of-thumb tuning methods and the model-based iterative schemes of controller refinement, considered in this thesis, are similar. In both instances, closed loop experiments are performed to evaluate performance and direct future controller adjustment, if required. Hence, the convergence of controller performance is obtained through experimentation and observation, as opposed to theoretical justification (Van den Hof and Schrama, 1994).

Remark 2.8.9 (Zang *et al*, 1995, Gevers, 1993). The underlying idea behind the iterative designs is not to carry out the iterations indefinitely, but rather to achieve closed loop performance enhancement in a few iterations. Therefore, in general, the iterative designs do not have a mathematical stopping criterion which defines when it is best to terminate the design process. Rather, the onus is on the designer to evaluate performance and monitor the relative magnitude of previous performance enhancements, and then make an informed decision on whether it worth continuing the iterative design effort. Therefore, this decision is not so much of technical decision as an common-sense economic one.

To summarise, many of the current iterative schemes seek to minimise the achieved performance, J^{ach}, indirectly, by performing a control-relevant closed loop identification followed by a control design during each iteration. Usually, closed loop identification is performed using prediction error methods. Each identification and control design involves an unconstrained minimisation which incorporates user-chosen design variables. Some iterative approaches require that identified models and enhanced controllers pass specific acceptance tests before the next stage proceeds, refer Figure 2.3 (Van den Hof and Schrama, 1994).

The three major iterative design methodologies reviewed in this thesis are :-

- the Zangscheme (Zang *et al*, 1995, 1992, 1991, Partanen and Bitmead, 1994b, 1993b), where closed loop identification methods using direct prediction error methods are employed to produce a control-relevant models for a not-so-cautious LQG control enhancement.

- an iterative scheme for high achieved performance using approximate identification and robust control design (Schrama and Bosgra, 1993, Schrama 1992a, 1992b, Schrama and Van den Hof, 1992). In its current form, this scheme employs a control-relevant normalised right coprime factor identification and H_∞ robust stability optimisation which guarantees a certain robust stability margin for the cautiously enhanced controller.

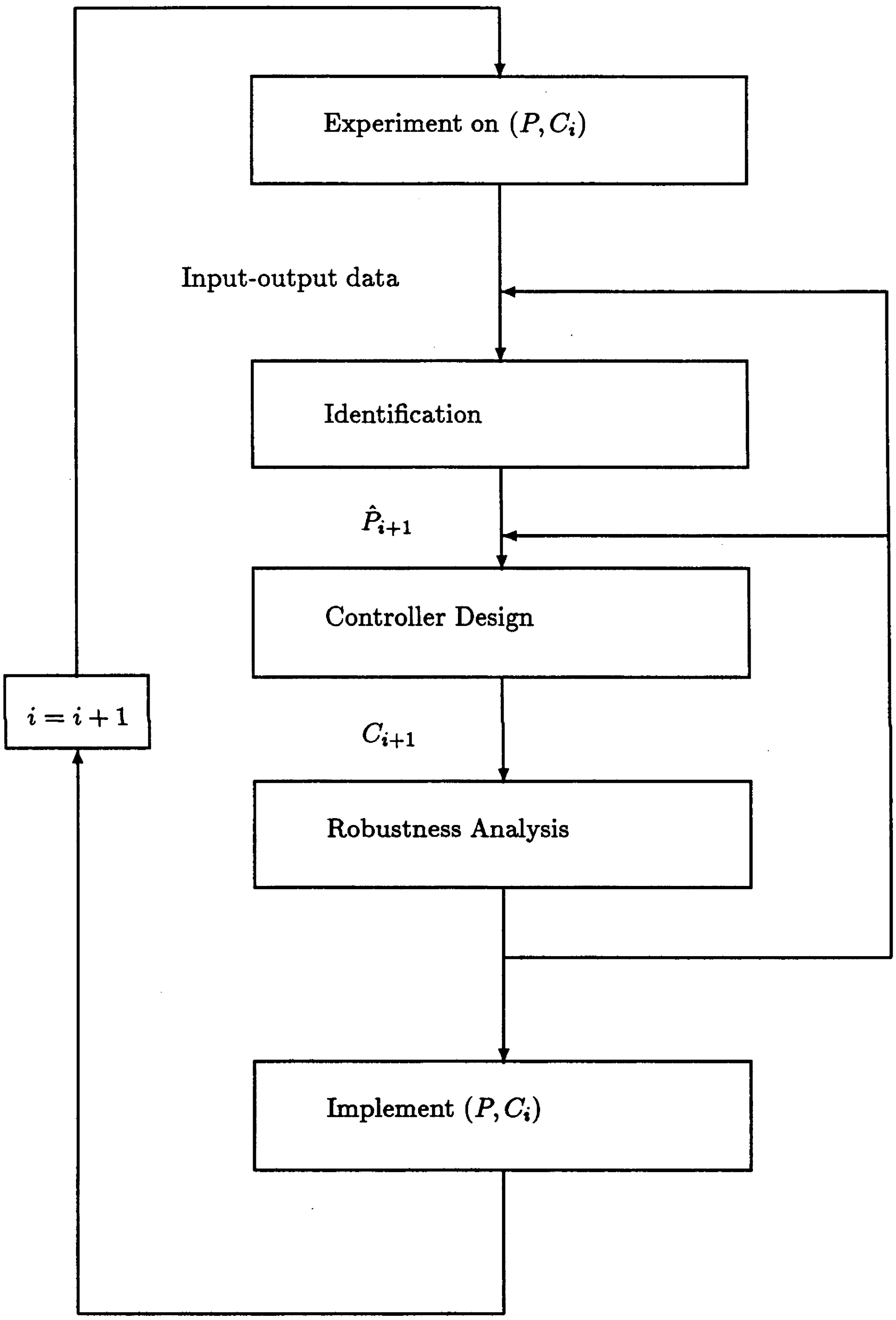

Figure 2.3: Iterative scheme of identification and control design.

- the iterative identification and control design for robust performance approach (Lee 1994, Lee *et al* 1993a, 1993b, Anderson and Kosut, 1991). This approach combines control-relevant dual Youla-parameter identification and subsequent model update with successive cautious Internal Model Control (IMC) designs aimed at extending the achieved closed loop bandwidth to attain high achieved control performance.

2.9 Chapter Conclusion

Iterative identification and control design has been presented as a practical method of controller refinement using readily available design tools. Justified thesis assumptions have restricted the consideration of the iterative design methods to the gradual off-line refinement of disturbance rejection controllers for unknown LTIFD systems.

The available iterative designs are primarily characterised by the control design criterion. However, before any model-based control design can be attempted, a control-relevant plant model is required. The next chapter investigates available methods of control-relevant closed loop identification used in main iterative designs.

Chapter 3

Closed Loop Identification

3.1 Chapter Motivation

Closed loop identification using prediction error methods features prominently in many iterative identification and control design schemes for controller refinement. Apart from prediction error identification methods there are not many other options for the identification of parametric plant models from closed loop input-output data. However, closed loop identification of input-output plant dynamics has its drawbacks. The theory of closed loop identification shows that even with plant models of sufficient complexity to describe the true system, the application of **direct** prediction error methods using closed loop input-output data may result in the identification of plant models which do not accurately describe the true system. Such plants models are termed biased. To overcome this bias problem, a number of **indirect** closed loop identification methods which are capable of delivering unbiased plant models (provided that the true system is in the model set) have been proposed.

This chapter reviews both direct and indirect methods to closed loop identification. However, before this review, the difference between indirect identification methods proposed during 1970s and those of a younger vintage are clarified.

3.2 Informative Experiments and Indirect Identification

The identifability of input-output plant dynamics from closed loop data is determined by the experimental conditions. That is, whether the input-output data is sufficiently informative to allow discrimination between any two models in the model set. Informative closed loop data sets can be obtained by performing closed loop experiments with either, sufficiently complex possibly time varying controllers, and/or the injection of extra persistent excitation at either the plant or controller input (Gustavsson *et al*, 1977, Ng *et al*, 1977, Söderström *et al*, 1976, Ljung *et al*, 1974).

In this thesis, attention is directed towards the sophisticated indirect closed loop identification methods of the late 1980s/early 1990s research harvest, in which identifiability is promoted exclusively through the injection of excitation signals rather than by switching controllers. These methods include (Van den Hof and Schrama, 1994, Gevers, 1993) :-

- the two-stage indirect method of transfer function estimation from closed loop data (Van den Hof and Schrama, 1993).
- dual Youla-parametrization methods (Hansen, 1989, Hansen *et al*, 1989, 1988, Schrama, 1992, Lee, 1994, Lee *et al*, 1993a, 1993b, 1992, Anderson and Kosut, 1991).
- normalised coprime factor identification methods (Van den Hof *et al*, 1993, de Callafon *et al*, 1994).

A common feature of these indirect methods is that they use not only the input-output data, $\{y, u\}$, but also the excitation signal, r, or an auxiliary signal that is a filtered version of $\{y, u\}$ or r. Hence the classification *indirect.* Note, that with direct prediction error methods, only the input-output data, (y, u), are used during the identification. However, these input-output data sequences are generated during a closed loop experiment with excitation injected to promote identifiability. This distinction will be made more evident shortly.

Remark 3.2.1 In some cases, the injection of additional excitation signals may not be permitted since excessive variance of the plant input signal may result. In such situations, it is possible to enhance closed loop identifiability by switching between several different controllers which give acceptable control performance (Ljung *et al*, 1974). Of course, acceptable control performance is not a pseudonym for high achieved control performance.

Remark 3.2.2 Traditional indirect approaches to closed loop identification of the 1970s (Söderström and Stoica, 1989), regarded the closed loop system as a whole, and, in general, identifiability was promoted by switching between different controllers to generate the plant input,

$$u(k) = -C_j y(k) + F_j r(k) \quad j = 1, 2, \ldots J,$$

during an identification experiment in which excitation, r, is also injected. F_j denotes a linear filter to frequency shape the excitation signal, and j denotes the j-th controller in a sequence of length, J, applied during the identification experiment. Ljung (1987) shows that the identification experiment will be sufficiently informative even if the excitation, $r(k)$, is not injected, provided the controllers, $\{C_j\}$, are different. With 1970's so named *indirect* identification method (Söderström *et al*, 1976, Ljung *et al*, 1974), open loop plant parameters were determined from closed loop parameters using knowledge of the controller. This method assumes that the external reference signals are measurable (if present). Another closed loop identification approach, the joint input-output method (Anderson and Gevers, 1982, Caines and Chan, 1975, Phadke and Wu, 1974), considers the input and output processes jointly as the output of a system driven by noise. Both plant and feedback dynamics are identified at the one time, with the plant dynamics retrieved through subsequent matrix manipulations. For the joint input-output method, the external excitation need not be measurable nor the controller known.

All three of the above listed recently proposed indirect closed loop identification methods could conceivably be used in an iterative identification and control design paradigm. The dual Youla-parametrization method is employed in iterative schemes of Lee *et al* (1993a), and has also been employed by Schrama (1992a). The two-stage indirect scheme has found utility in the Zangscheme (Partanen and Bitmead, 1995) and is applicable to the other mentioned iterative schemes as it resembles a robust control performance criterion (Van den Hof and Schrama, 1994). The normalised coprime factor identification method is, now, the preferred identification for the iterative scheme of Schrama (1992a), Van den Hof *et al* (1993). The three indirect identification methods will be investigated in detail in this chapter, but first, closed loop identification using direct prediction error methods will be considered.

3.3 Direct Prediction Error Method

The analysis presented of prediction error methods for closed loop identification closely follows the methodology of Ljung (1987). Identification of SISO systems is considered since the corresponding results for multi-variable systems are, in general, similar, albeit that the notation used in the corresponding multi-variable formulae are more complex. Figure 2.1, page 14 shows the closed loop system under consideration during the identification of a plant model using closed loop input-output data.

The system, $\mathcal{S}$, in Section 2.3, can be modelled by a parametrized set of models, $\mathcal{M}$, written as :-

$$\mathcal{M}: \quad y(k) = \hat{P}(z,\theta)u(k) + \hat{H}(z,\theta)e'(k), \tag{3.1}$$

where $e'(k)$ is a white noise process and $\hat{P}(z,\theta)$ and $\hat{H}(z,\theta)$ are strictly proper and proper rational transfer functions, respectively. The set of possible values for the parameter vector, θ, for a given model structure, $\mathcal{M}$, ranges over the set of admissible values, $D_{\mathcal{M}}$, which in turn is an open subset of a d-dimensional vector space, $\mathcal{R}^d$, where d is length of the parameter vector, θ, i.e.

$$\theta \in D_{\mathcal{M}} \subset \mathcal{R}^{d_\theta}. \tag{3.2}$$

AR, ARX, ARMA, ARMAX, ARIMAX, FIR are examples of equation error model structures. Other model structures include output error (OE) and Box-Jenkins (BJ).

Remark 3.3.1 If $\mathcal{S} \in \mathcal{M}$, then it is said that the system is in the model set. In general, this thesis deals with restricted complexity models which implies that the system is not in the model set, i.e. $\mathcal{S} \notin \mathcal{M}$.

The prediction error associated with the model description, (3.1), is

$$\begin{aligned} \epsilon(k,\theta) &= \hat{H}^{-1}(z,\theta)[y(k) - \hat{P}(z,\theta)u(k)] \\ &= \hat{H}^{-1}(z,\theta)[(P(z) - \hat{P}(z,\theta))u(k) + v(k)]. \end{aligned} \tag{3.3}$$

The '*best*' model in the model set, $\mathcal{M}$, is derived from the selected parameter vector $\theta^\star$ that minimises a sum-squared prediction error criterion,

$$V_N(\theta) = \frac{1}{N}\sum_{t=1}^{N}[\epsilon^f(k,\theta)]^2, \quad \epsilon^f(k,\theta) = D(z)\epsilon_k(\theta), \tag{3.4}$$

where $\epsilon^f(k,\theta)$ are the prediction errors filtered through a stable linear filter with transfer function, $D(z)$, chosen by the user to effect a frequency weighted model fit. For SISO and multi-input multi-output (MISO) systems, the data filter, D, can be applied to the input-output data, $\{y,u\}$, prior to an unweighted criterion minimisation. N is the length of the data sequences available for identification.

To study open loop identification, Ljung (1987) substitutes from (3.3) into (3.4), with allowance for a data filter, before appealing to (respectively): the quasi-stationarity of the signals, the independence of input $u(k)$ and disturbance $v(k)$, and Parseval's formula; to establish the well known open loop frequency domain identification formula :-

$$V_N(\theta) = \frac{1}{2\pi}\int_{-\pi}^{\pi}\left\{|P(e^{j\omega}) - \hat{P}(e^{j\omega},\theta)|^2\Phi_r(\omega) + \Phi_v(\omega)\right\}\frac{D(e^{j\omega})}{\hat{H}(e^{j\omega},\theta)}d\omega. \tag{3.5}$$

The criterion, (3.5), provides a characterisation of the bias, i.e. the difference between the true plant and identified plant model as measured by $|P - \hat{P}(\theta)|$ to first order. Wahlberg and Ljung (1986) illustrate how the choices of data filters, disturbance models, sampling instant, and prediction horizon affect the distribution of the plant model bias across the frequency spectrum.

Open loop identification can be tuned to ensure that the criterion minimisation is independent of the unknown disturbance spectrum. This is achieved by simply choosing a model structure with a fixed disturbance model, e.g. $\hat{H}(\theta) = 1$ or $\hat{H}(\theta) = L(z)$, where $L(z)$ is fixed known stable and stably invertible linear filter. Provided the true plant is in the model set, the identified plant model will be unbiased. Unfortunately with closed loop identification, as will become evident later, a simple choice of model structure which could prevent the unknown disturbance spectrum from contributing bias to resultant model parameter estimates does not exist.

Remark 3.3.2 To effect identification with fixed disturbance models, the inverse of the fixed disturbance model is included in the data filter realisation.

With closed loop data, the assumption of independence of $u(k)$ and $v(k)$ is no longer valid and one must take into account their correlation due to the presence of the controller in the feedback path, refer Figure 2.1, page 14. As with the open loop case, closed loop identification uses the input-output signals, $\{y,u\}$, to derive a θ via the minimisation of (3.4). The nature of closed loop identification minimisation is now summarised by the following theorem, first derived by Gunnarsson (1988), and stated in this more revealing form by Partanen and Bitmead (1993a).

Theorem 3.1 *Consider the control system in Figure 2.1, where the plant input signal $u(k)$ is given by,*

$$u(k) = -C(z)y(k) + r(k).$$

Assume that,

- *$r(k)$ is a quasi-stationary excitation signal added to the plant input,*
- *the disturbance process $v(k)$ is quasi-stationary and independent from $r(k)$,*
- *the closed loop system is asymptotically stable.*

Then the identification cost criterion may be written as

$$\begin{aligned} V_N(\theta) &= \frac{1}{2\pi}\int_{-\pi}^{\pi} \left\{|P(e^{j\omega}) - \hat{P}(e^{j\omega},\theta)|^2\Phi_r(\omega) + |1 + C(e^{j\omega})\hat{P}(e^{j\omega},\theta)|^2\Phi_v(\omega)\right\} \\ &\times \frac{|D(e^{j\omega})|^2}{|1 + C(e^{j\omega})P(e^{j\omega})|^2|\hat{H}(e^{j\omega},\theta)|^2}\, d\omega. \end{aligned} \tag{3.6}$$

Proof Under the Theorem conditions, the control signal is given by

$$\begin{aligned} u(k) &= r(k) - C(z)v(k) - C(z)P(z)u(k), \\ &= [1 + C(z)P(z)]^{-1}r(k) - [1 + C(z)P(z)]^{-1}C(z)\, v(k). \end{aligned} \tag{3.7}$$

and, hence, the prediction error is

$$\begin{aligned} \epsilon(k,\theta) &= \hat{H}^{-1}(z)\left\{(P(z) - \hat{P}(z,\theta))(1 + C(z)P(z))^{-1}[r(k) - C(z)\, v(k)] + v(k)\right\} \\ &= \hat{H}^{-1}(z)\left[(P(z) - \hat{P}(z,\theta))\, r(k) + (1 + C(z)\hat{P}(z,\theta))\, v(k)\right](1 + C(z)P(z))^{-1}, \end{aligned} \tag{3.8}$$

where now $\epsilon(k,\theta)$ has been expressed as a sum of two independent signals, $r(k)$ and $v(k)$. The transposition of the prediction error, $\epsilon(k,\theta)$, to multi-variable plant models is examined more fully in Appendix A. One may appeal directly to the methods of Ljung outlined above to derive the Theorem via Parseval's formula. ■

Remark 3.3.3 Some researchers claim that the results of Theorem 3.1 are well-known and have been written down many times before, and that a similar expression appears in Gevers (1993). Let it be recorded here that Bob Bitmead and the author wrote down the frequency domain criterion, (3.6), on May 31, 1991. This criterion featured prominently in the Partanen and Bitmead (1993a) paper, which was first submitted to the 12th IFAC World Congress paper review panel in June, 1992.

The closed loop identification cost criterion, (3.6), is fundamental to understanding the effect of the closed loop on the minimisation search and the mechanisms available to the user to manipulate the identification. Criterion (3.6) clearly demonstrates the interplay between the closed loop and identification design variables; plant excitation, data filter, disturbance model. Appropriate data filter and excitation selection can be used to modify the closed loop identification criterion into one which resembles a performance degradation criterion, thereby, making closed loop identification control-relevant, c.f. Section 2.8.

Remark 3.3.4 Rivera *et al* (1992) present a systematic procedure for the non-iterative design of control-relevant data filters to be employed during open loop identification. Although a control-relevant data filter depends upon the plant and disturbance models to be estimated, a simplified non-iterative design was found to be not only convenient, but more importantly adequate in most instances. Non-iterative control-relevant data filter designs in preference to more complicated iterative designs, have been successfully utilised in closed loop identification (Zang *et al*, 1995).

The criterion also highlights the importance of choosing an appropriate excitation signal as a mechanism for the identifier to fit $\hat{P}(\theta) \approx P$, in the frequency band of interest, as opposed to the tendency to fit $\hat{P}(\theta) = -C^{-1}$, especially when the disturbance process has considerable energy. The selection of identification design variables for the sugar cane crushing control problem is detailed in Chapter 6.

Unfortunately for closed loop identification using direct prediction error methods, no standard model structures can be selected which ensure that the model fitting process is independent of the disturbance spectrum (Van den Hof and Schrama, 1994, Gevers, 1993).

The role that the unknown disturbance spectrum plays in closed loop identification can be seen by considering alternative form for the prediction error expression in (3.8) (Gevers, 1993),

$$\begin{aligned}\epsilon(k,\theta) &= D\hat{H}^{-1}\Big[(P-\hat{P}(\theta))\,r(k)+[H(1+C\hat{P}(\theta))-\hat{H}(\theta)(1+CP)]\,e(k)\Big](1+CP)^{-1}\\ &\quad + De(k). \end{aligned} \tag{3.9}$$

Arguments in ω have been deliberately omitted. Since the disturbance and the disturbance model numerator polynomials are monic and $e(k)$ is a sequence of independent random variables, the three separate terms on the right-hand side are independent. The last term, $De(k)$, is independent of θ, therefore the minimisation of $V_N(\theta)$ is equivalent to the minimisation of,

$$\begin{aligned}V_N^*(\theta) &= \frac{1}{2\pi}\int_{-\pi}^{\pi}\Big\{|P-\hat{P}(\theta)|^2\Phi_r(\omega)\\ &\quad + |H(1+C\hat{P}(\theta))-\hat{H}(\theta)(1+CP)|^2\sigma_e\Big\}\frac{|D|^2}{|1+CP|^2|\hat{H}(\theta)|^2}\,d\omega. \end{aligned} \tag{3.10}$$

It is apparent that from the minimisation of (3.10), the plant model will be biased in the case where either a parametrized model structure is used that is incapable of modelling the true disturbance spectrum, or when a fixed inexact approximation of the disturbance is used. As mentioned in the Section 3.1, indirect closed loop identification methods have been motivated by a need to acquire an unbiased plant model from closed loop input-output data, regardless of the accuracy of the disturbance models. From a control design perspective, the need for unbiased plant models without regard for the quality of the disturbance model is suggestive of design for stability robustness. With a controller design for performance robustness, the accuracy between the designed and achieved closed loop systems is the issue, and not the individual accuracies of the plant and disturbance models.

Remark 3.3.5 Åström and Wittenmark (1973) consider a self-tuning regulator consisting of a Least Squares parameter estimator and a minimum variance control law for controlling an unknown LTI system. Åström and Wittenmark (1973) show that if the model parameter estimates converge, then the optimal minimum variance control law is obtained. This is despite the fact that the least squares model parameter estimates are known to be biased. This example shows that in some cases biased plant models may not necessarily have a detrimental effect on the achieved closed loop performance.

The above frequency domain characterisation (3.10) gives the bias error in estimating the plant model. Modelling errors are made up of bias and variance errors. Given an unbiased plant model estimated, the variance of the estimated plant model is approximately proportional to (Ljung, 1987, 1985) :-

$$\frac{n}{N}\Phi_v(\omega)\begin{pmatrix}\Phi_u(\omega) & \Phi_{ue}(\omega)\\ \Phi_{ue}(-\omega) & \sigma_e\end{pmatrix}, \tag{3.11}$$

where n is the model order, Φ_{ue} is the cross-spectrum between the plant input and the white noise process, e_k. The formula applies to both open loop identification ($\Phi_{ue} = 0$) and closed loop identification ($\Phi_{ue} \neq 0$). Minimising bias and variance are conflicting requirements, since increasing model order could reduce bias errors, yet variance errors are proportional to the model order.

The best model structure (in the sense that total model error is minimised) is a tradeoff between minimising bias and variance errors, that is one which gives a bias error of the same size as the variance error (Hjalmarsson and Ljung, 1992, Söderström and Stoica, 1989, Ljung, 1987). This observation is direct consequence of the principle of parsimony associated with model identification, recall Remark 2.8.7.

Remark 3.3.6 Hjalmarsson and Ljung (1992) show that the above traditional estimate of plant model parameter's variance error, (3.11), is not reliable if there exists bias error. Hjalmarsson and Ljung (1992) present a recursive procedure for the consistent estimation of the model parameter's variance.

Remark 3.3.7 (Ljung, 1993). In general, the iterative identification and control design methods concentrate on minimising bias errors and neglecting variance errors, therefore the iterative design procedures are not optimal. Whether the bias errors outweigh the variance depends upon signal to noise ratios, the number of data, and the degree of approximation.

Remark 3.3.8 There exist a number of controller design methods which consider model variance errors as part of the design procedure. Kosut (1995) constructs a family of unfalsified bias/variance tradeoff curves from which a family of uncertainty models is obtained for a robust controller design, as part of an iterative identification and control design. Hansen *et al* (1989) take variance errors into account in the formulation of a closed loop experiment design for identification purposes. Yuan and Ljung (1985) have studied the design of an optimal open loop identification experiment in which contributions from both bias and variance errors are minimised.

Next, an indirect closed loop identification method in which two open loop identifications are required to realise the plant model transfer function estimates.

3.4 Two-stage Indirect Method

The two-stage indirect identification is one of many identification methods which can be used in the iterative design schemes of Schrama (1992a). This approach is considered here, since it has been successfully employed in developing feedback controllers for the sugar cane crushing process (Partanen and Bitmead, 1995). The two-stage closed loop identification method has been employed in other industrial applications, e.g. wind turbine systems (van Baars, 1994), continuous crystallisation process (Eek *et al*, 1994), distillation column (Van der Klauw, 1994). The results of application to the sugar cane crushing process are detailed in Chapter 6.

A two-stage indirect method for transfer function estimation from closed loop data has been proposed by Van den Hof and Schrama (1993). Using independently parametrized plant and disturbance models, this identification method gives a tunable expression for the bias of the identified model. This is not the case with direct prediction error methods for closed loop identification, where the bias error $P(e^{j\omega}) - \hat{P}(e^{j\omega}, \theta)$ depends upon the disturbance spectrum, $\Phi_v(\omega)$. Recall (3.10).

The two-stage indirect method treats closed loop identification as two open loop identification problems. Central to this method is the independence between the persistently exciting and measurable plant excitation, $r(k)$, and the unknown additive output disturbance, $v(k)$. A parametrized set of models, $\mathcal{M}_1$, defined for the first identification stage, allows the formulation of a prediction error identification of the closed loop sensitivity function, $S = (1 + CP)^{-1}$, and a mixed sensitivity function, $V = -(1 + CP)^{-1}CH$, using the plant input, $u(k)$, and the excitation signal, $r(k)$. $\mathcal{M}_1$ is defined as,

$$\mathcal{M}_1: \quad u(k) = \hat{S}(z,\beta)r(k) + \hat{V}(z,\zeta)\epsilon^u(k), \quad \beta \in D^{\beta}_{\mathcal{M}_1} \subset \mathcal{R}^{d_\beta}, \quad \zeta \in D^{\zeta}_{\mathcal{M}_1} \subset \mathcal{R}^{d_\zeta}, \quad (3.12)$$

where $\epsilon^u(k)$ is the one-step-ahead prediction error of $u(k)$. $\hat{S}(z,\beta), \hat{V}(z,\zeta)$, can be independently parametrized by employing a Box-Jenkins model structure. As with the direct prediction error method of closed loop identification, it is assumed that the closed loop system is stable.

Since the excitation, $r(k)$, and the disturbance, $v(k)$, are independent, the model fitting is equivalent to that of open loop identification. The effect of the excitation and disturbance on the plant input can now be separated. The component of the plant input which depends only on the excitation, $r(k)$, is defined as $\hat{u}^r(k)$, and can generated by a simulation of the form,

$$\hat{u}^r(k) = \hat{S}(z,\beta)r(k). \tag{3.13}$$

In the second identification stage, a parametrized set of models, $\mathcal{M}_2$, is defined to permit the identification of a plant model, $\hat{P}$, and disturbance model, $\hat{H}_{vs}$, using the plant output, $y(k)$, and the excitation-dependent plant input, $\hat{u}^r(k)$. $\mathcal{M}_2$ is defined as,

$$\mathcal{M}_2: \quad y(k) = \hat{P}(z,\theta)\hat{u}^r(k) + \hat{H}_{vs}(z,\eta)\epsilon^y(k), \quad \theta \in D^{\theta}_{\mathcal{M}_2} \subset \mathcal{R}^{d_\theta}, \quad \eta \in D^{\eta}_{\mathcal{M}_2} \subset \mathcal{R}^{d_\eta}, \tag{3.14}$$

where $\epsilon^y(k)$ is the prediction error of $y(k)$. The signals on the right-hand side of the (3.14) are uncorrelated, therefore the second identification, like the first identification, is also an open loop one. As in the first stage, the transfer function estimates, $\hat{P}(z,\theta), \hat{H}(z,\theta)$, can be parametrized independently using a Box-Jenkins model structure.

Under the assumption, $\hat{S}(z,\beta) = S(z)$, the identified disturbance model, $\hat{H}_{vs}$, will model the true disturbance, H, weighted by the true sensitivity, S, since,

$$\begin{aligned} y(k) &= Pu(k) + He(k), & (3.15) \\ &= P(\hat{u}^r(k) + Ve(k)) + He(k), & \\ &= P\hat{u}^r(k) + SHe(k). & (3.16) \end{aligned}$$

Remark 3.4.1 Since the two-stage indirect method uses a model structure in which the plant and disturbance models are independently parametrized, the associated one-step-ahead predictor will always be stable, even if the true plant is unstable. Therefore, with unstable plants, the two-stage indirect identification method will deliver a stable plant model which minimises a sum-squared prediction error criterion.

Van den Hof and Schrama (1993) show that the bias distribution of $\hat{P}(z,\theta)$ from the second identification step is dependent on the first identification. Furthermore, provided the estimated sensitivity function mismatch is made sufficiently small by selecting sufficient order in the model structure to describe the sensitivity function dynamics, the plant transfer function can be estimated accurately. Van den Hof and Schrama (1993) characterise the frequency bias in model estimation as,

$$V_N(\theta) = \int_{-\pi}^{\pi}\left\{\left|[P(e^{j\omega}) - \hat{P}(e^{j\omega},\theta)]S(e^{j\omega}) + \hat{P}(e^{j\omega},\theta)[S(e^{j\omega}) - \hat{S}(e^{j\omega},\beta)]\right|^2\Phi_r(\omega)\right.$$
$$\left. + \quad |S(e^{j\omega})|^2\Phi_v(\omega)\right\}\frac{|D(e^{j\omega})|^2}{|L(e^{j\omega})|^2}\,d\omega, \tag{3.17}$$

where $L(z)$ is a fixed disturbance model used during the second identification.

Equation (3.17) shows that bias distribution of $\hat{P}(z,\theta)$ is dependent on the accuracy of the sensitivity function estimated during the first identification and is independent of disturbance spectrum, Φ_v. Van den Hof and Schrama (1993) suggest that the sensitivity function can be accurately identified using high order FIR models, or, alternatively, a series of expansion of orthonormal basis functions, e.g. Laguerre and Kautz (Heuberger *et al*, 1995, Wahlberg, 1994).

Given a sufficiently accurate sensitivity estimate, i.e.

$$\hat{S}(z,\beta) \to S(z),$$

the two-stage identification tends to minimise,

$$V_N(\theta) \to \frac{1}{2\pi}\int_{-\pi}^{\pi}\left\{\left|[P(e^{j\omega}) - \hat{P}(e^{j\omega},\theta)]S(e^{j\omega})\right|^2\Phi_r(\omega) + |S(e^{j\omega})|^2\Phi_v(\omega)\right\}\frac{|D(e^{j\omega})|^2}{|L(e^{j\omega})|^2}\,d\omega. \tag{3.18}$$

Clearly, (3.18) has control-relevant form since the model mismatch is weighted by the achieved closed loop sensitivity. Criterion, (3.18), can be used to motivate the selection of appropriate excitation and data filtering signals.

3.5 Dual Youla-parametrization

This approach to closed loop identification allows the formulation of a solution methodology which requires the generation of intermediate signals using known filters, open loop identification, and plant and disturbance model transfer function updates according to simple formulae. Again, the preference for utilising open loop identification to avoid bias problems induced by the incorrectness of the disturbance model is evident.

Like the previously presented closed loop identification methods, this method assumes that the current controller, C, is fixed and stabilises the true plant, P. It also assumes that the controller is known. The controller, C, can be used to parametrize the set of all stabilised plants, $\mathcal{P}_{rs}$. This is the dual equivalent of the Youla-parametrization (Youla, 1976a, 1976b) for the set of all stabilising controllers for a given plant, P. The individual plants in set of all stabilised plants, $\mathcal{P}_{rs}$, can be represented by fractional coprime factorisations. The algebraic theory of coprime factorisations provides a mathematical tool for analysing the stability of feedback systems (Vidyasagar, 1985, Desoer *et al*, 1980). Other related applications of algebraic theory and coprime factorisation include robust stabilisation (McFarlane and Glover, 1990, Bongers and Bosgra, 1990), model and controller reduction, (Bongers and Bosgra, 1990, McFarlane *et al*, 1990, Liu *et al*, 1990, Liu and Anderson, 1986). The use of fractional coprime factorisations for identification was proposed by Hansen *et al* (1988) with a view to closed loop experiment design.

Control-relevant identification utilising the dual Youla parametrization with left coprime factorisations has been explored by Hansen (1989), Hansen *et al* (1989), whilst Schrama (1992a, 1991c) employs right coprime factorisations. The two methods are considered to be duals of each other. Schrama (1992a) applies this identification method in an iterative identification and control design scheme in which the controller design is undertaken by H_∞ robust optimisation design. In alternative iterative design, Lee (1994), Lee *et al* (1993a, 1993b, 1992), adopt the Hansen method of the closed loop identification to obtain plant models to be used in an IMC control design. This section details features of control-relevant closed loop identification using the dual Youla-parametrization with left coprime factors, as per Hansen (1989a). To simplify the analysis which follows the distinction between right and left coprime factorisations is avoided. In any case, the distinction between left and right coprime factors evanesces for LTIFD SISO systems. This is not the case for LTIFD multi-variable or non-linear systems.

Definition 3.5.1 *(Vidyasagar, 1985). Two transfer function factors* $(N, D) \in \mathcal{H}_\infty$ *are coprime if and only if there exist Bezout factors,* (X, Y)*, such that*

$$X(z)N(z) + Y(z)D(z) = I. \tag{3.19}$$

Remark 3.5.1 Coprimeness implies that the factors do not possess any common unstable factors. A fractional coprime factor representation of a transfer function, either stable and unstable, is not unique.

Remark 3.5.2 $\mathcal{H}_\infty$ refers to the set of transfer function which are analytic on or outside the unit circle, i.e. transfer functions which are stable. $\mathcal{H}_\infty$ is the Hardy space.

Remark 3.5.3 Coprime factors, (N, D), are normalised if

$$N^T(z^{-1})N(z) + D^T(z^{-1})D(z) = I. \tag{3.20}$$

Theorem 3.2 *(Hansen, 1989a). Let* $\frac{X}{Y}$ *be a coprime factorisation of any controller,* C*, and let* $\frac{N_0}{D_0}$ *be a coprime factorisation of any nominal plant model,* $\hat{P}_0$*, which is stabilised by* C*. Then, the set of all plant models,* $\mathcal{P}_{rs}$*, stabilised by* C *can be parametrized by the pair,* (R, S_{yp})*, as in*

$$\mathcal{P}_{rs} : y(k) = \hat{P}(R)u(k) + \hat{H}(R, S_{yp})w(k), \tag{3.21}$$

with R *being stable and* S_{yp} *being stable and stably invertible.* $w(k)$ *is a sequence of independent random variables with zero mean and covariance,* σ_w*. For a particular* (R, S_{yp}) *pair, the plant and disturbance model transfer functions are determined by,*

$$\hat{P}(R) = \frac{N_0 + RY}{D_0 - RX} = \frac{N}{D}, \tag{3.22}$$

$$\hat{H}(R, S_{yp}) = \frac{S_{yp}}{D_0 - RX} = \frac{M}{D}. \tag{3.23}$$

Furthermore, (3.22) and (3.23), are coprime factorisations of the $\hat{P}(R)$ *and* $\hat{H}(R, S_{yp})$*, respectively. The parameters,* (R, S_{yp})*, are given by*

$$R = \frac{D_0 N - N_0 D}{XN + YD}, \tag{3.24}$$

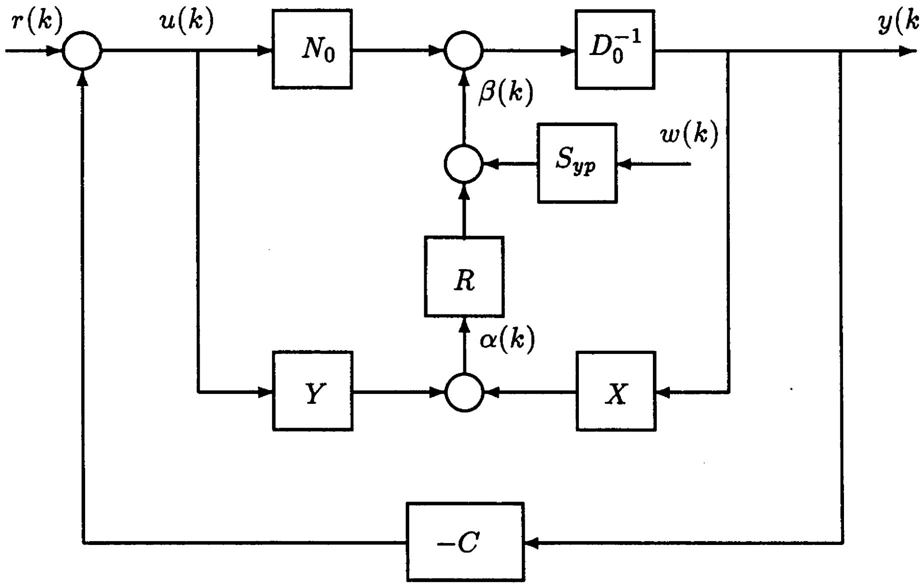

Figure 3.1: Dual-Youla parametrization of the achieved closed loop system.

$$S_{yp} = \frac{XN_0 + YD_0}{XN + YD} M. \tag{3.25}$$

Remark 3.5.4 Zang *et al* (1995), use the same concept of identifying plant models stabilised by the current controller, albeit using a different parametrization, to promote a particular choice of identification design variables according to robust stability requirements.

Remark 3.5.5 Hansen (1989), Hansen *et al* (1989) use the parametrization pair, (R, S). Since, in this thesis, S is already assigned to the sensitivity function, a parameterization pair, (R, S_{yp}), is adopted.

The (R, S_{yp}) parametrization of the system, $\mathcal{P}_{rs}$, results in the closed loop block diagram shown in Figure 3.1. Hansen (1989a) shows that the parameter pair, (R, S_{yp}), can be used to define a parametrized set of models, $\mathcal{M}_{rs}$, for which each model is parametrized by ρ, that is,

$$\mathcal{M}_{rs}: \qquad \beta(k) = \hat{R}(\rho)\alpha(k) + \hat{S}_{yp}(\rho)w(k), \tag{3.26}$$

where

$$\beta(k) = D_0 y(k) - N_0 u(k), \tag{3.27}$$

$$\alpha(k) \quad = \quad Yu(k) + Xy(k), \tag{3.28}$$

are readily computable from the closed loop signals and the fractional description of a nominal plant model, $\hat{P}_0$, and the controller, C. Since the signals, $\alpha(k)$ and $w(k)$, are independent, (3.26) forms the basis for an open loop identification. The independence of signals, $\alpha(k)$ and $w(k)$, will become evident shortly.

To gain an insight into the fractional approach in terms of the original transfer functions P, $\hat{P}_0$, and C, first recall the closed loop signal expressions for Figure 2.1, that is

$$y(k) = \frac{P}{1+CP}r(k) + \frac{1}{1+CP}v(k), \tag{3.29}$$

$$u(k) = \frac{1}{1+CP}r(k) - \frac{C}{1+CP}v(k), \tag{3.30}$$

where in this instance the disturbance signal, $v(k)$, depends upon the white noise process, $w(k)$, i.e. $v(k) = Hw(k)$. Secondly, choose the coprime factors of $\hat{P}_0$ and C as

$$N_0 \quad = \quad \hat{P}_0; \quad D_0 = 1, \tag{3.31}$$

$$X \quad = \quad \frac{C}{1+C\hat{P}_0}; \quad Y = \frac{1}{1+C\hat{P}_0}. \tag{3.32}$$

For this choice of coprime factors to be valid it is assumed that $\hat{P}_0$ is stable. Note, that this choice of coprime factors satisfies the Bezout identity. Other factorisation choices are possible.

The fractional approach to closed loop identification identifies, in an open loop manner, a Youla parameter, R, which represents a closed loop weighted mismatch between the true plant and the current plant model, i.e.

$$R = \frac{(P - \hat{P}_0)(1 + C\hat{P}_0)}{1+CP}. \tag{3.33}$$

This can be verified by substituting the selected coprime factorisations into (3.24). Similarly, an expression for S_{yp},

$$S_{yp} = \frac{1+C\hat{P}}{1+CP}H, \tag{3.34}$$

can be derived by substituting the chosen coprime factorisations into (3.25).

Substitution of the signal expressions (3.29), (3.30) and the coprime factors (3.31), (3.32) into (3.27) and (3.28) yields

$$\beta(k) = \frac{P-\hat{P}_0}{1+CP}r(k) + \frac{H(1+C\hat{P}_0)}{1+CP}w(k), \tag{3.35}$$

$$\alpha(k) = \frac{1}{1+C\hat{P}_0}r(k), \tag{3.36}$$

From equation, (3.36), it is obvious that the signals, $\alpha(k)$ and $w(k)$, are independent.

Remark 3.5.6 $\alpha(k)$ has a clear resemblance to the excitation dependent plant input, $\hat{u}^r(k)$, generated for the second identification stage of the two-stage indirect method. The difference is that $\alpha(k)$ is dependent upon a transfer function calculated given a nominal plant model, $\hat{P}_0$, and the controller, C, whilst with $\hat{u}^r(k)$ the transfer function is estimated, and is therefore dependent upon the achieved closed loop system (P, C).

The identification criterion associated with identifying a ρ parametrized pair, (R, S_{yp}), is,

$$\begin{aligned} V_N(\rho) &= \int_{-\pi}^{\pi} \left\{ \left| \frac{P(e^{j\omega}) - \hat{P}_0(e^{j\omega})}{1+C(e^{j\omega})P(e^{j\omega})} - \frac{\hat{R}(e^{j\omega},\rho)}{1+C(e^{j\omega})\hat{P}(e^{j\omega})} \right|^2 \Phi_r(\omega) \right. \\ &\quad \left. + \left| \frac{1+C(e^{j\omega})\hat{P}(e^{j\omega})}{1+C(e^{j\omega})P(e^{j\omega})} \right|^2 \Phi_v(\omega) \right\} \frac{D(e^{j\omega})}{|\hat{S}_{yp}(e^{j\omega},\rho)|^2}\, d\omega, \end{aligned} \tag{3.37}$$

For asymptotically large amounts of data, the dual-Youla parametrization method of realising a plant model, $\hat{P}(\theta)$, does not depend upon the nominal plant model, $\hat{P}_0$, or its factorisation, since the only requirement upon the nominal plant model is that it is stabilised by the controller, C (Hansen, 1989a).

The identified model mismatch, $\hat{R}(\rho)$, is then used to update the plant model according to (3.24). Due to the dual Youla-parametrization the updated plant model will be stabilised by the controller, C. As with the two-stage indirect identification method, the plant model will be unbiased since the identification minimisation search is independent of the unknown disturbance spectrum (for a fixed S_{yp}).

It is evident that the identification criterion, (3.37), has a control-relevant form. The control-relevant nature of this identification method has been exploited for control design by Schrama (1992a) and Lee *et al* (1993a, 1993b).

Despite, the apparent advantages of this identification method, it is hampered by the fact that the order of updated plant model is generally much larger, at least twice, that of the original nominal model. For controller refinement using restricted complexity controller designs, the procedure is further complicated by an additional, however necessary, model or controller reduction step.

3.6 Normalised Coprime Factor Identification

An alternative scheme which avoids the excessive model order involves the direct identification of normalised coprime factors, N, D, associated with a coprime factor description of the plant. In this framework the plant is described by the normalised right coprime factorisation, $P = ND^{-1}$. One reason for employing normalised coprime factors is that, in general, if the plant, P, has McMillan degree, n_p, then normalised coprime factors of P will also have McMillan degree, n_p. Hence, problems associated with excessive model order are avoided. Again, the analysis which follows does not make use of the fact that the coprime factorisation is right coprime. This scheme was proposed by Van den Hof *et al* (1993), with recent extensions in de Callafon *et al*, (1994).

Like the other indirect methods it involves the generation of an auxiliary signal,

$$x(k) = Fr(k), \tag{3.38}$$

where F is a stable and stably invertible filter. This signal is akin to $\hat{u}^r(k)$ of the two-stage method and $\alpha(k)$ used in dual-Youla parametrization approach.

By selecting coprime factors N, D which describe the plant, P, as

$$N = \frac{P}{1+CP}F^{-1}; \quad D = \frac{1}{1+CP}F^{-1}, \tag{3.39}$$

the expressions for the plant output, $y(k)$, and the plant input, $u(k)$, become,

$$\begin{aligned} y(k) &= Nx(k) + SHe(k), && (3.40) \\ u(k) &= Dx(k) - CSHe(k). && (3.41) \end{aligned}$$

Recall that $S = (1 + CP)^{-1}$. Since $x(k)$ and $e(k)$ are uncorrelated, the resulting identification of parametrized coprime factors, $\hat{N}, \hat{D}$, can be performed in an open loop way.

In order to apply standard open loop identification methods with $x(k)$ as the input and $[y(k)\ u(k)]$ as the output, the filter, F, must be stable. Naturally, it is assumed that the identification experiment was performed on a stable closed loop system (P, C). Van den Hof *et al* (1994) show that a filter, F, can be constructed from a given nominal plant model, $\hat{P}_0$, which is stabilised by the known controller, C. Using the same choice of plant coprime factors as in (3.31), the choice for F simplifies to

$$F = \frac{1}{1 + C\hat{P}_0}. \tag{3.42}$$

The open loop identification of the θ parametrized coprime factors, $\hat{N}(\theta), \hat{D}(\theta)$, amounts to a constrained minimisation of filtered sum-squared prediction errors. The related identification cost criterion is,

$$\theta^* = \arg\min_\theta \frac{1}{2\pi}\int_{-\pi}^{\pi} \begin{bmatrix} N - \hat{N}(\theta) \\ D - \hat{D}(\theta) \end{bmatrix}^* \begin{bmatrix} |L_1|^2 & 0 \\ 0 & |L_2|^2 \end{bmatrix} \begin{bmatrix} N - \hat{N}(\theta) \\ D - \hat{D}(\theta) \end{bmatrix} \Phi_x(\omega)d\omega, \tag{3.43}$$

where L_1, L_2 are data filters which frequency weight the coprime factor model fit. The minimisation is constrained to the particular parametrization of the coprime factors corresponding to (3.39), i.e.

$$\begin{bmatrix} \hat{N}(\theta) \\ \hat{D}(\theta) \end{bmatrix} = \begin{bmatrix} \frac{\hat{P}(\theta)}{(1+C\hat{P}(\theta))}F^{-1} \\ \frac{1}{(1+C\hat{P}(\theta))}F^{-1} \end{bmatrix}. \tag{3.44}$$

The parametrization constraint induces a control-relevant identification with a criterion (Van den Hof and Schrama, 1994),

$$\begin{aligned} \theta^* &= \arg\min_\theta \frac{1}{2\pi}\int_{-\pi}^{\pi} \Big\{ |P(1+CP)^{-1} - \hat{P}(\theta)(1+CP(\theta))^{-1}|^2 |L_1|^2 \\ &+ |(1+CP)^{-1} - (1+C\hat{P}(\theta))^{-1}|^2 |L_2|^2 \Big\} \Phi_r(\omega)d\omega. \end{aligned} \tag{3.45}$$

Van den Hof *et al* (1993) employ a similar strategy to the two-stage method to solve this constrained identification problem. Included in this strategy is an intermediate step to normalise the coprime factors. It should be noted that the identification of the coprime factors, $\hat{N}, \hat{D}$, strongly depends on the nominal model, $\hat{P}_0$.

3.7 Chapter Conclusion

Many industrial feedback control redesign problems require an input-output plant model. For the purposes of maintaining stability or for economic reasons of maintaining production, this model must be identified from closed loop input-output data using either direct or indirect methods of closed loop identification. With the indirect closed loop identification methods, it is well known that the unknown disturbance spectrum will not bias the plant model. This is not the case with direct closed loop identification.

The selection of identification design variables, excitation and data filtering, are fundamental to understanding the outcome of modelling process. Frequency domain identification criteria characterise the role of excitation and data filtering during this process. With direct prediction error methods, although the excitation signal is not used explicitly to fit the model, its effect on the plant's response must dominate over that of the disturbance process, if the plant dynamics are to be captured. With indirect methods, the plant dynamics are automatically exposed by the explicit use of the excitation signals, filtered by either estimated or calculated closed loop transfer functions, during the model fitting process. Data filtering is used to frequency-weight the model in both direct and indirect closed loop identification.

Closed loop identification is a vital component of iterative identification and control design schemes for controller refinement. In the next chapter, three major approaches to iterative identification and control design are reviewed.

Chapter 4

Iterative Identification and Control Design

4.1 Chapter Motivation

Many excellent surveys of iterative identification and control designs are available (Van den Hof and Schrama, 1994, Gevers, 1993, Bitmead, 1993) These schemes have also been reviewed in the PhD dissertations of Lee, 1994, and Schrama, 1992a. The emphasis in this chapter is toward a concise, as opposed to technically detailed, presentation which outlines the prominent features with each of the iterative methods.

As mentioned in Chapter 2, the chosen control design criterion can be used to motivate a control-relevant identification. Both identification and control design for three major iterative design schemes is reviewed. In addition, a number of other significant approaches to iterative design are briefly discussed.

It should be noted that the analysis presented in this chapter is specific to single-input single-output (SISO) systems. Extension to the multi-variable case is relatively straightforward, but at the price of increased notational complexity.

4.2 The Zangscheme

The Zangscheme iterative design has been developed at the Australian National University, Canberra, Australia, the Université Catholique de Louvain, Belgium, Louvain-la-Neuve, Belgium, and at the Curtin University of Technology, Perth, Australia (Zang *et*, 1995, 1992, 1991, Zang, 1992, Partanen and Bitmead, 1993b). The scheme incorporates LQG control design and control-relevant closed loop identification using direct prediction error methods.

4.2.1 Control Design

The aim of any iterative identification and controller design is to produce, with each iteration, an enhanced controller which, when used to control the true plant, improves the achieved performance, as measured by some predefined criterion. With the Zangscheme, the achieved control performance is given by evaluating the following LQ criterion,

$$J^{ach} = \lim_{N\to\infty} \frac{1}{N} E\left[\sum_{k=1}^{N} y(k)^2 + \lambda u(k)^2\right], \tag{4.1}$$

using input-output signals, $\{u(k), y(k)\}$, available from the achieved closed loop depicted in Figure 2.1, page 14 (when $r(k) = 0$). $E[\cdot]$ denotes expectation.

However, with a standard non-frequency-weighted LQG design, a model-based controller selected to operate on the true plant, minimises the following LQ design performance,

$$J^{des} = \lim_{N\to\infty} \frac{1}{N} E\left[\sum_{k=1}^{N} [y^c(k)]^2 + \lambda [u^c(k)]^2\right], \tag{4.2}$$

where the input-output signals, $\{u^c(k), y^c(k)\}$, are those of the designed closed loop depicted in Figure 2.2, page 25. The designed closed loop differs from the achieved closed loop system since only estimates of the true plant and disturbance are available. Clearly, model mismatch will exist, hence the achieved and designed performances cannot be equivalent.

Although the controller design cannot minimise the achieved performance, J^{ach} (since the plant and disturbances are unknown), the controller design should nevertheless minimise a criterion which resembles J^{ach}. This can be realised with an LQ criterion in which the signals $y^c(k)$ and $u^c(k)$ are replaced with filtered versions $F_1 y^c(k)$ and $F_2 u^c(k)$, respectively. The frequency weightings, F_1 and F_2, are defined as

$$F_1 = \{\frac{\Phi_y}{\Phi_{y^c}}\}^{1/2} \quad ; \quad F_2 = \{\frac{\Phi_u}{\Phi_{u^c}}\}^{1/2}, \tag{4.3}$$

where Φ_u, Φ_y are the spectra of the true plant input, $u(k)$, and plant output, $y(k)$, from the achieved closed loop system. Similarly Φ_{u^c}, Φ_{y^c} are the spectra of the simulated plant model input, $u^c(k)$, and the simulated plant model output, $y^c(k)$, from the designed closed loop system.

The controller minimisation associated with modified LQ criterion containing the frequency weightings, F_1, F_2, is given by,

$$C_{i+1} = \arg \min_{C \in \mathcal{C}} \frac{1}{N} \left[\sum_{k=1}^{N} [F_1(P, \hat{P}_i, C_i) y_k^c(\hat{P}_{i+1}, C)]^2 + \lambda [F_2(P, \hat{P}_i, C_i) u_k^c(\hat{P}_{i+1}, C)]^2 \right], \quad (4.4)$$

where $\hat{P}_{i+1}$ is the plant model of the current iteration, whilst $\hat{P}_i$, is the plant model from the previous iteration. Note that the time index parameter, k, moves to the subscript location when signals are explicitly shown to be dependent on transfer function quantities.

Remark 4.2.1 The original LQ design criterion, J^{des}, given by equation (4.2), can be considered to be a special case of the frequency-weighted LQ criterion in (4.4).

Remark 4.2.2 (Zang *et al*, 1995) The frequency weighted LQG control design is directed entirely toward performance enhancement on the achieved closed loop system. Hence, there are no robust stability guarantees. A robust stability aspect can be included into the Zangscheme during the model adjustment phase. This is considered further in Section 4.2.2.

Remark 4.2.3 The frequency weighted LQG controller design criterion (4.4) shows that the signals generated in the controller design are not synchronised with those used to estimate the frequency weightings. That is, the frequency weightings depend upon $(P, \hat{P}_i, C_i)$, whilst the closed loop signals, $\{y_k^c, u_k^c\}$, associated with the enhanced controller, C_{i+1}, depends upon $(P, \hat{P}_{i+1}, C_{i+1})$. This discrepancy is used in Chapter 7 to motivate a variant to the original Zangscheme.

Remark 4.2.4 The Zangscheme employs the certainty equivalence control design. Therefore the resultant controller cannot be considered to be cautious. However, as will be shown in Chapter 7, the magnitude of the adjustment to the current controller parameters can be made cautiously, if the effect of the frequency weightings is user-scalable.

For the SISO disturbance rejection problem (no reference tracking), the frequency weightings, F_1 and F_2, are equal (Zang *et al*, 1992). Define a frequency weighting, F, as,

$$F \triangleq F_1 = F_2. \quad (4.5)$$

Fixed order auto-regressive (AR) models are used to approximate the numerator and denominator of the frequency weighting F. AR models are stable and stably invertible. Although the stably invertible feature is not necessary for SISO frequency weighted LQG controller designs, invertible frequency weightings are required for multi-variable designs. Since the frequency weightings are used in a controller design to emphasise those frequency bands in which the current closed loop performance is poor and de-emphasise those bands in which it is good, third order AR models of the frequency weightings are sufficiently accurate for this purpose. Higher order frequency weightings produce higher order controllers. The additional accuracy captured with high order frequency weightings may evanesce after the high order controller is necessarily reduced to a low order controller of fixed length prior to implementation. Furthermore, for cautious controller enhancement, as will be shown later in this thesis, the frequency weightings should be detuned, negating any additional accuracy reflected in high order frequency weightings. The detuned frequency weightings still affect the desired control persuasion.

Zang *et al* (1995) show that the frequency-weighted LQ SISO disturbance rejection problem can be recast as a standard non-frequency-weighted LQ problem by transforming the plant and disturbance models,

$$\hat{\hat{P}} = \hat{P}, \hat{\hat{H}} = F\hat{H}. \tag{4.6}$$

This transformation allows the designer to use the existing LQG controller design algorithms available in many control design software packages (Grace *et al*, 1992). The standard non-frequency-weighted LQG design on $(\hat{\hat{P}}, \hat{\hat{H}})$ delivers an optimal controller $\bar{C}$ which is the controller solution, C, of the frequency-weighted LQG problem in (4.4) (Zang *et al*, 1995).

4.2.2 Identification

The identification part of the iterative designs seeks to minimise the contribution of the performance degradation, J^{pd}, in the triangle inequalities, (2.14) and (2.15). As motivated in the Section 2.7, this is attempted by performing a control-relevant closed loop identification. Minimisation of the performance degradation using direct prediction error methods induces a particular choice of identification design variables, excitation spectrum and data filter transfer function.

As noted in Remark 4.2.2, the controller enhancement step of the Zangscheme is oriented towards improving the performance on the achieved closed loop system through a frequency weighted controller design. In general, the frequency weighting will emphasise those frequency bands where the plant model mismatch is poor (Zang *et al*, 1995). Therefore, the resultant frequency weighted LQG controller will assign a large control gain in those frequency bands where the model fit is poor, with possibly detrimental consequences for the stability of the supposedly enhanced achieved closed loop system. In those circumstances where robust stability may be compromised, performing an identification which minimises the performance degradation will, in general, not improve the accuracy of the fitted models, and therefore is likely to exacerbate further the stability problems. In such situations, it might be advantageous to perform an identification oriented toward robust stability rather one in which the performance degradation is minimised.

Remark 4.2.5 With the Zangscheme, as has just been alluded, performance enhancement may be at the expense losing of stability. This observation is contrary to the expectations of traditional robust control where a design which is performance oriented also meets stability requirements.

The model adjustment step of the Zangscheme can be performed in two different ways depending upon user-requirements for robust stability or robust performance. The selection of identification design variables, excitation spectrum and data filtering, is now examined in detail for robust performance and robust stability oriented identification.

Robust Performance

Robust performance (Doyle *et al*, 1992) is an attempt to preserve controller performance in the designed closed loop when the controller is implemented in the achieved closed loop system. In a controller design, robust performance, involves miminising a nominal performance criterion and checking to ensure that nominal performance design specifications are not violated in the presence of model mismatch.

In the above definition of robust performance for controller design the plant model is the fixed quantity and the controller is the variable of the design. Conversely, to formulate an identification for robust performance, the controller becomes the fixed component and the plant model is the variable component. Assume that closed loop input-output data from an identification experiment performed on current achieved closed loop system, (P, C_{i-1}), is available for identification. The aim behind a robust performance oriented identification is to fit a plant model, $\hat{P}_i$, which causes closed loop systems, $(\hat{P}_i, C_{i-1})$ and (P, C_{i-1}), to have similar performances. That is, the newly identified plant model preserves the performance of the current controller, C_{i-1}, on the system, P, when the system, P, is replaced by $\hat{P}_{i-1}$. In order that C_{i-1} maintains similar performance on both P and $\hat{P}_i$, the plant model, $\hat{P}_i$, should be identified by minimising the performance degradation. For LQG disturbance rejection the performance degradation criterion is,

$$J_{H_2}^{pd} = \lim_{N \to \infty} \frac{1}{N} E \sum_{t=1}^{N} (y(k) - y^c(k))^2 + \lambda(u(k) - u^c(k))^2. \tag{4.7}$$

Remark 4.2.6 Criterion, (4.7) was the only criterion minimised during the model adjustment step in the original version of the Zangscheme (Zang *et al*, 1991).

Remark 4.2.7 Van den Klauw *et al* (1994) uses criterion (4.7) to propose a generalised closed-loop identification method which is shown to induce a variety of closed loop identification methods, including direct and the two-stage indirect methods, depending upon the particular parametrizations for $\{y^c(k), u^c(k)\}$.

The following Lemma outlines the choice of excitation spectrum and data filtering required to realise a prediction error identification in which the same criterion as given by (4.7) is minimised.

Lemma 4.1 *(Zang* et al, *1995). Let the closed loop signals, $\{y(k), u(k), r(k), v(k)\}$ and $\{y^c(k), u^c(k)\}$, be defined respectively by Figures 2.1 (page 14) and 2.2 (page 25). Fix $\hat{H}(e^{j\omega}, \theta) = H(e^{j\omega})$. Assume that the performance degradation criterion, $J_{H_2}^{pd}$ equation (4.7), is to be minimised over a set of θ parametrized plant models, $\mathcal{M}$, using the direct prediction error method of closed loop identification. Under these conditions, the identification of new plant model, $\hat{P}_i$, requires,*

- *closed input-output data, $\{y(k), u(k)\}$, from an identification experiment performed on the achieved closed loop system, (P, H, C_{i-1}), with an injected excitation signal, $r(k)$, possessing a spectrum,*

$$\Phi_r(\omega) = \gamma^2 |C(e^{j\omega})|^2 \Phi_v(w) = \gamma^2 |C(e^{j\omega})|^2 |H(e^{j\omega})|^2, \quad \forall\ \omega \in [-\pi, \pi),$$

and,

- *a data filter* $D(z,\theta) = \hat{H}(z,\theta)G(z)(1 + C_{i-1}(z)\hat{P}_{i-1}(z,\theta))^{-1}$, *where* $G(z)$ *is a stable filter obtained from the factorisation problem,*

$$G(z)G^*(z^{-1}) = 1 + \lambda C_{i-1}(z)C^*_{i-1}(z^{-1}).$$

■

Remark 4.2.8 Zang *et al* (1995) warn that this identification is based on signals whose spectra are determined by the disturbance process alone, recall $\Phi_r(\omega) = \gamma^2|C(e^{j\omega})|^2\Phi_v(\omega)$ from Lemma 4.1. Hence, with a closed loop identification performed with design variables chosen as per Lemma 4.1, there are no stability guarantees, in the form of an offline test, prior to the implementation of the next controller.

Remark 4.2.9 Zang *et al* (1995) show that in the frequency domain, the performance degradation criterion, (4.7), can be written as,

$$J^{pd}_{H_2} = \frac{1}{2\pi}\int_{-\pi}^{\pi} |W|^2 \left| \frac{H}{1 + C_{i-1}P} - \frac{\hat{H}(\theta)}{1 + C_{i-1}\hat{P}_i(\theta)} \right|^2 d\omega, \tag{4.8}$$

where

$$|W|^2 \triangleq 1 + \lambda|C_{i-1}|^2. \tag{4.9}$$

If a fixed disturbance model is selected such that $\hat{H}(\theta) \neq H$, as will usually be the case if the true disturbance is unknown, then the minimisation of $J^{pd}_{H_2}$ with respect to $\hat{P}_i(\theta)$ cannot be solved using the standard prediction error methods associated with either direct or indirect closed loop identification. However, an approximate solution to this optimisation problem can be motivated by considering an alternative time domain criterion for $J^{pd}_{H_2}$, i.e.

$$J^{pd}_{H_2} = \lim_{N\to\infty} \frac{1}{N} E \sum_{k=1}^{N} \left[W(z)(y_k - \frac{\hat{P}_i(\theta)}{1 + C\hat{P}_i(\theta)} e_k) \right]^2, \tag{4.10}$$

This criterion cannot be minimised directly since the white noise signal, $e(k)$, is not measurable. However, given an estimate of $e(k)$, it is conceivable that by using optimisation methods possibly subject to closed loop stability constraints, a plant model, $\hat{P}_i(\theta)$, which approximately minimises the performance degradation criterion, (4.10), could be obtained.

For a fixed, yet inexact, disturbance model, the plant model, $\hat{P}_i(\theta)$, which minimises the performance degradation, (4.8 is mostly likely to be biased. This reinforces the notion that biased plant models are not necessarily detrimental for control purposes, recall Remark 3.3.5. This is the subject of ongoing research.

An estimate of e_k could be obtained from,

$$\hat{e}(k) = \hat{Q}^{-1}y(k), \tag{4.11}$$

where $\hat{Q}$ is an identified estimate of $H(1+CP)^{-1}$ obtained by modelling the operational output, $y(k)$, of the achieved closed loop system with $r(k) = 0$, as being generated by an ARMA process.

Robust Stability

Robust stability is defined by Doyle *et al* (1992), as an attempt to preserve the asymptotic stability of the designed closed loop when the designed controller is implemented in the achieved closed loop. When designing the i-th controller, $C_i(\hat{P}_i)$, with robust stability in mind, a sufficient condition for the stability of the achieved closed loop, $(P, C_i(\hat{P}_i))$, is

$$\left\| \frac{P - \hat{P}_i}{\hat{P}_i} \times \frac{\hat{P}_i C_i}{1 + C_i \hat{P}_i} \right\|_\infty < 1, \tag{4.12}$$

with both $\frac{C_i \hat{P}_i}{1+C_i \hat{P}_i}$ and $\frac{P-\hat{P}_i}{\hat{P}_i}$ stable. For a robust controller design, C_i is the variable component whilst the plant, P and the plant model, $\hat{P}_i$, are fixed quantities.

Conversely, when identifying a new plant model, $\hat{P}_i$, using data from the achieved closed loop, (P, C_{i-1}), the identified $\hat{P}_i$ will still be stabilised by C_{i-1} provided,

$$J^{pd}_{H_\infty} = \left\| \frac{P - \hat{P}_i}{P} \times \frac{C_{i-1} P}{1 + C_{i-1} P} \right\|_\infty < 1, \tag{4.13}$$

with both $\frac{C_i P}{1+C_i P}$ and $\frac{P-\hat{P}_i}{P}$ stable. This condition relates the variable of the model adjustment phase, $\hat{P}_i$, to the fixed quantities, P and C_{i-1}.

Both criteria, (4.12) and (4.13), are ∞-norm criteria, and as such need to be satisfied uniformly across all frequencies. Practical necessity forces the use of L_2 prediction error identification methods for many applications. A prediction error identification which minimises a 2-norm version of the robust stability criteria for identification, (4.13), has been formulated by Zang *et al* (1995). Zang *et al* (1995) have also formulated an assessment of model quality for control which can be directly evaluated from an alternative expression for the robust stability criterion (4.13), prior to controller implementation. The selection of the identification design variables and the model quality assessment for robust stability are summarised by the following lemma.

Lemma 4.2 *(Zang* et al, *1995). With LQG controller design there is no robust stability guarantee. However by taking a plant model identified with :-*

- $D(z,\theta) = \hat{H}(z)$, *where* $\hat{H}(z) \approx H(z)$.
- $\Phi_r(\omega) = \gamma^2 |C(e^{j\omega})|^2 \gg |\Phi_v(\omega)|, \quad \forall\ \omega \in [-\pi, \pi)$.
- *a feedback controller,* $C(z) = C_{i-1}(z)$, *which stabilises both* $P(z)$ *and* $\hat{P}_{i-1}(z)$,

then, the new plant model, $\hat{P}_i(e^{j\omega}, \theta)$, *where*

$$\theta = \arg\min_{\theta} \left\| \frac{C(e^{j\omega})|P(e^{j\omega}) - \hat{P}_i(e^{j\omega},\theta)|}{1 + C(e^{j\omega})P(e^{j\omega})} \right\|_2, \tag{4.14}$$

is delivered from an identification primarily directed towards finding a new model $\hat{P}_i$, *which is also stabilised by* C_{i-1}. *Now when the controller,* C, *itself is updated from* C_{i-1} *to* C_i, *there exists the following test for robust stability, i.e. whether* P *will be stabilised by* C_i,

$$\left\| \left(\frac{1}{F_i(z)} - 1 \right) \left(\frac{(C_i(1 + C_{i-1}\hat{P}_i)}{(C_{i-1}(1 + C_i\hat{P}_i)} \right) \right\|_{\infty} < 1, \tag{4.15}$$

provided the degree of the frequency weighting, F_i, *which approximates,*

$$\{\frac{\Phi_{y^c}}{\Phi_y}\}^{1/2} = \frac{\{\Phi_{u^c}}{\Phi_u}\}^{1/2}$$

is sufficiently large. ■

Remark 4.2.10 Robust stability conditions (4.12) and (4.12) reflect sufficient conditions for stability robustness using multiplicative model mismatch descriptions of the form, $\frac{P-\hat{P}_i}{\hat{P}_i}$ and $\frac{\hat{P}_i-P}{P}$. In Lemma 4.2, the identification criterion, (4.14), expressed in terms of an additive model mismatch, $|P - \hat{P}_i|$, is identical to that for multiplicative model mismatch. Nevertheless, optimising (4.14) corresponds to minimising additive rather than multiplicative model mismatch. Therefore, the stability robustness of the identified plant model, $\hat{P}_i$, is not easily established. Hence, the use of the word *primarily* in the Lemma 4.1 when describing what the identification delivers.

The formula (4.15) holds regardless of how C_i was derived, other than that it stabilises $\hat{P}_i$. The term in the frequency weighting, $(F_i^{-1} - 1)$, suggests caution when using frequency weightings which exhibit large deviations from unity.

A direct H_2 robust control design for C_i would be preferable. However, this is not possible with a standard LQG design due to the presence of an observer. Unlike LQ controllers, stability margins for LQG controllers cannot be guaranteed (Doyle, 1978) and robust stability may be lost. Partial rehabilitation of the stability margin for LQG controllers can be rallied through Loop Transfer Recovery (LTR) techniques, refer Bitmead *et al* (1990), hence the use of LTR in the Zangscheme controller enhancement phase.

Remark 4.2.11 There exist some H_2 robust control design methods which guarantee a certain level of performance for a given structured model uncertainty (Bernhardsson, 1992a, 1992b). Since, it is difficult to obtain and validate model uncertainty estimates for complex industrial processes, recall Remark 2.6.5, controller design methods which do not require model uncertainty estimates may be preferable.

4.2.3 Iterative Design

To summarise, the Zangscheme features :-

- a totally quadratic approach to identification and control design.
- a not-so-cautious controller enhancement.
- identification design variables chosen to reflect robust stability or robust performance requirements for the controller design.
- a robust stability test.
- a resultant restricted complexity controller with regulated controller order.
- applicability to multi-variable systems.

4.3 Delft Iterative Design

An iterative identification and controller design using H_∞-design robustness optimisation has been developed at the Mechanical Engineering Systems and Control Group, Delft University of Technology, Delft, The Netherlands (Schrama, 1992a, 1992b, Schrama and Van den Hof, 1992, Schrama and Bosgra, 1993). This method features a control-relevant identification, cautious controller enhancement, and a specific robustness test performed to prior to on-line controller implementation.

4.3.1 Controller Design

Before outlining the controller design method, the generalised closed loop transfer function matrix is defined.

Definition 4.3.1 *The four-block closed loop transfer function matrix, $T(\hat{P},C)$, for the generalised H_∞ optimal control problem is defined as,*

$$T(\hat{P},C) \triangleq \begin{bmatrix} \hat{P} \\ I \end{bmatrix} [I + C\hat{P}]^{-1} [C \quad I], \tag{4.16}$$

$$T(\hat{P},C) = \begin{bmatrix} \hat{P}(1+C\hat{P})^{-1}C & \hat{P}(1+C\hat{P})^{-1} \\ (1+C\hat{P})^{-1}C & (1+C\hat{P})^{-1} \end{bmatrix}, \tag{4.17}$$

In order to meet the requirements for high achieved control performance, as given in Section 2.8, the Delft iterative design scheme uses a robust control design in which the enhanced controller results from the following optimisation,

$$C_{i+1} = \arg\min_{C\in\mathcal{C}} \|T(\alpha_{i+1}\hat{P}_{i+1}, C/\alpha_{i+1})\|_\infty, \tag{4.18}$$

where α_{i+1} is a constant positive scalar design parameter. The design parameter, α, allows the designer to exercise caution during the controller design, since the designed or nominal closed loop bandwidth will be close to that of the nominal model, $\alpha\hat{P}$. Large values of α, i.e. minimal caution, accomplish high nominal performance which is a requirement for high achieved control performance, recall Section 2.7. Unfortunately in some instances, high nominal performance is known to be incompatible with achieving the specified closed loop bandwidth on the true system (Schrama, 1992a, McFarlane and Glover, 1988). That is, the selection of the design parameter, α, determines the nominal performance and robust stability tradeoff.

Remark 4.3.1 The iterative scheme of Lee *et al* (1993a) also proceeds with cautious controller enhancement by gradually extending the nominal closed loop bandwidth via a single IMC controller design parameter.

In order to achieve a maximal robust stability margin, the controller design problem is formulated to optimise robust stability against additive pertubations to a normalised coprime factor description of the nominal plant model (Bongers, 1994, Bongers and Bosgra, 1990, Glover and McFarlane, 1989, McFarlane and Glover, 1992, 1990, 1988). This robust stability optimisation approach to controller design involves defining an uncertainty set with restrictions on the coprime factors and on the associated coprime factor perturbations.

Definition 4.3.2 *Let $(\hat{N},\hat{D})$ be a normalised right coprime factor (nrcf) representation of the nominal plant model, i.e. $\hat{P}(z) = \hat{N}(z)\hat{D}^{-1}(z)$. Let $(\Delta N, \Delta D)$ be stable additive coprime factor perturbations. An uncertainty set, $\mathcal{P}_\Delta(\hat{P},\gamma)$, (strictly) restricted in size by a scalar metric, γ, is defined as,*

$$\mathcal{P}_\Delta(\hat{P},\gamma) \triangleq \{\hat{P}_\Delta = (\hat{N}+\Delta N)(\hat{D}+\Delta D)^{-1} \quad : \quad \left\| \begin{matrix} \Delta N \\ \Delta D \end{matrix} \right\|_\infty < \gamma\}, \tag{4.19}$$

where $\hat{P}_\Delta$ refers to perturbed nominal plant model.

Given an uncertainty set in Definition 4.3.2, the robust stability optimal control problem is stated in the following theorem (Bongers and Bosgra, 1990, Bongers 1994, McFarlane and Glover, 1988).

Theorem 4.1 *Given a nominal plant model, $\hat{P}$, described by normal coprime factors, $(\hat{N},\hat{D})$, and stabilised by the controller, C, let there exist stable perturbations, $(\Delta N, \Delta D)$, such that the true plant, P, satisfies the description,*

$$P = (\hat{N}+\Delta N)(\hat{D}+\Delta D)^{-1}.$$

Then, the controller, C, stabilises the true plant, P, for all stable coprime perturbations, $(\Delta N, \Delta D)$, if $\|T(\hat{P},C)\|_\infty \le \gamma^{-1}$.

Remark 4.3.2 Theorem 4.1 gives a robust stability test, i.e. is $\|T(\hat{P},C)\|_\infty \le \gamma^{-1}$, which can be computed prior to on-line controller implementation (Schrama and Bongers, 1991). Since Theorem 4.1 gives a sufficient condition, the robustness test, in general, will be quite conservative. In practice, with complex industrial processes in which it is difficult to quantify the bound associated with the size of the uncertainty set, therefore the above robustness test is of limited utility.

Remark 4.3.3 For a given controller, C, which stabilises the nominal closed loop, it is possible to quantify the size of a plant uncertainty set for which C is a stabilising controller. The size of this set defines a guaranteed stability margin. Bongers and Bosgra (1990) show that Theorem 4.1 induces a stability margin for a specific set size or distance measure known as the gap metric (El-Sakkary , 1985). Conversely, Georgiou and Smith (1990) show that an optimal robust stability margin as measured by the gap metric can be obtained by a robust stability optimisation using normalised coprime factor perturbations. The selection of a particular distance measure determines the relative conservativeness of the stability margin, and therefore the relative size of the uncertainty set stabilised by the controller, C. If the uncertainty set is relatively small, compared with the number of possible plants stabilised by the controller, C, then in such circumstances there exists the strong possibility that the robust stability test will fail under false pretenses.

Robust stability optimisation for large uncertainty set size is detrimental to high achieved control performance, recall Section 2.6. Therefore, although the controller enhancement phase of the Delft iterative design is directed toward robust stability, the model identification is focussed toward obtaining plant model which is compatible with a control design for high achieved performance.

4.3.2 Model Identification

The analysis so far for the Delft iterative design has concentrated upon the control design aspect which assumes the availability of a plant model. In Section 2.8, it was motivated that the requirement of high achieved control performance also necessitated the identification of a compatible plant model, $\hat{P}_{i+1}$, in a control-relevant manner by minimising performance degradation. The performance degradation criterion associated with the Delft iterative scheme is,

$$\hat{P}_{i+1} = \arg\min_{\hat{P}\in\mathcal{P}} \|T(\alpha_i P, C_{i+1}/\alpha_i) - T(\alpha_i \hat{P}, C_{i+1}/\alpha_i)\|_\infty, \tag{4.20}$$

where $\hat{P}$ has a right coprime factor description description.

Remark 4.3.4 At each new control design step, the design parameter, α, is gradually increased to enhance nominal performance. A gradual increase implies caution necessary to ensure that the performance degradation remains acceptably small compared with the nominal performance. In practice, such a comparison can only be performed with an approximate estimate of the new performance degradation. This comparison provides the designer with estimated lower and upper bounds for the achieved performance and hence is an indicator of potential control performance.

H_∞ identification methods to solve the above identification are still in their infancy, and, at the time that this iterative design method was proposed, only existed in a conceptual context. Therefore, under these mitigating circumstances, Schrama (1992a), Schrama and Van den Hof (1992), adopted an L_2 identification method to minimise a 2-norm version of the performance degradation criterion, (4.20). L_∞ consistency results for L_2 estimators (Caines and Baykal-Gürsoy, 1989) suggests that prediction error identification methods will produce a good plant model, in L_∞.

In early versions of this iterative scheme, identification of the plant coprime factors was undertaken using frequency domain data. Subsequent versions employed the dual Youla-parametrization approach to indirect closed loop identification using time domain data. The current version employs the normalised coprime factor method. Normalised coprime factor identification was reviewed in Section 3.6.

Van den Hof and Schrama (1994) show that normalised coprime factor identification results in the constrained minimisation of a performance degradation criterion of the form,

$$T(P,C) - T(\hat{P},C_i) = \arg\min_{\theta} \begin{bmatrix} N - \hat{N}(\theta)F^{-1}C_i & N - \hat{N}(\theta)F^{-1} \\ D - \hat{D}(\theta)F^{-1}C_i & D - \hat{D}(\theta)F^{-1} \end{bmatrix}, \tag{4.21}$$

where F is the stable and stably invertible filter described by equation (3.42).

4.3.3 Iterative Design

The primary iterative design involves model identification followed by controller design with associated model validation, robust stability, and performance indicator tests. For a fixed design parameter, α, Schrama (1992a) postulates an advanced iterative design in which a single iteration consists of repeated model identifications and controller designs.

Model identification and control design are repeated until there are only negligible changes to the model and controller parameters. The advantage of the advanced iterative scheme over the primary scheme is that the rate at which achieved control performance improves is significantly faster.

To summarise, the key features of this iterative scheme are (Bitmead, 1993):

- the use of H_∞ robust control design to minimise a four block sensitivity matrix.
- the design parameter, α, which determines the nominal performance and robust stability tradeoff. This allows for cautious controller enhancement.
- a control-relevant L_2 identification to minimise performance degradation.
- a robust stability test which can be evaluated prior to online controller implementation.
- a performance indicator test from which estimates of the upper and lower bounds on the achieved performance can be calculated prior to controller implementation.
- applicability to multi-variable systems.

4.4 Internal Model Control (IMC) Iterative Design

An iterative identification and control design for robust performance has been developed at the Australian National University, Canberra, Australia, and Integrated System Inc., Santa Clara, USA (Lee, 1994, Lee *et al*, 1993a, 1993b, 1992, Anderson and Kosut, 1991). This approach performs closed loop identification using the dual-Youla parametrization and controller enhancement using IMC continuous time control design (Morari and Zafiriou, 1989). This iterative scheme is only applicable to single-input single-output (SISO) systems.

4.4.1 Control Design

The control design objective is to minimise the deviation of the closed loop complementary sensitivity, $T = \frac{CP}{1+CP}$, from a desired value, T_d, i.e.

$$C_{i+1} = \arg\min_{C\in\mathcal{C}} \|\frac{CP}{1+CP} - T_d\|_\infty, \tag{4.22}$$

in the face of model uncertainties.

As with the Delft iterative design, this approach incorporates a scalar closed loop bandwidth parameter, λ_j, into the control design. The bandwidth parameter, λ_j, is progressively increased until the achieved closed loop performance as measured by the difference between achieved and desired step response tests is found to be inadequate. At this point, the current plant model is deemed inadequate and a new plant model is re-identified. Again, a succession of controller designs with increasing closed loop bandwidths is undertaken.

Remark 4.4.1 With this IMC iterative design, a natural choice for the desired complementary function is one which incorporates the closed loop bandwidth parameter, λ_j, for example,

$$T_d = \left(\frac{\lambda_j}{s+\lambda_j}\right)^{n+1}, \tag{4.23}$$

where n is a prespecified integer which determines the roll-off rate. Lee *et al* (1993a) chooses to fix the roll-off rate design parameter by making it equal to the relative degree of the plant model plus one. This results in a strictly proper controller, which guarantees zero gain at infinite frequency.

Remark 4.4.2 This iterative design method is supposedly based upon the manner in which humans learn to sailboard[1] (Anderson and Kosut, 1991). Apparently, humans start with a feedback control system of moderate bandwidth, then through experimentation learn to control and direct a sailboard over a gradually increasing bandwidth. The author as a sailboarder with over 10 years experience in the sport believes that most sailboarders require only a low gain moderate bandwidth feedback control system to stabilise the unstable sailboard plant. A sailboarder applying large control actions at high speeds, invariably ends up in the drink. The converse of this is the sailboarder who appears to have all the time in the world and exerts little effort to direct the sailboard even in heavy conditions. A sailboarder achieves performance enhancement by predicting the action of the disturbance process, e.g. waves, winds. The behaviour of the disturbance can be readily observed by human senses of sight, touch, and hearing, primarily. *A priori* knowledge also plays a role in predicting the effect of the disturbances. The impact of the

[1] The sport of sailboarding is often incorrectly designated as windsurfing. The popularity of the term *windsurfing* stems from the trademark name of an early vintage model of sailboards, Windsurfer^{TM}.

predicted disturbances upon the sailboard can then either be, minimised or maximised, as desired through small control adjustments. The human sailboarder who relies purely on feedback control, without any feedforward prediction of disturbance behaviour, invariably, in frustration, gives up the sport very wet.

IMC controllers are a special case of Youla-parametrization of all stabilising controllers since IMC control design is only valid for stable plants (Morari and Zafiriou, 1989). A similiar robust stability margin result to that of the H_∞ controller design given by Theorem 4.1 exists for IMC control. The corresponding IMC control robust stability result is given in the following theorem.

Theorem 4.2 *(Morari and Zafiriou, 1989). Let $\hat{P}$ be a nominal plant, which is stabilised by the controller, C. $\hat{P}$ is also a member of the plant uncertainty set,*

$$\mathcal{P}_\Delta = P_\Delta : \quad |P(e^{j\omega}) - \hat{P}(e^{j\omega})| \leq l_a(\omega), \tag{4.24}$$

where all member plants in the uncertainty set, $\mathcal{P}_\Delta$, have the same number of unstable poles. Then, the controller, C, stabilises the true plant, $P \in \mathcal{P}_\Delta$, if the complementary sensitivity function, $\hat{T} = \frac{\hat{P}C}{1+\hat{P}C}$, satisfies,

$$\|\hat{T}(\hat{P}, C)\|_\infty \leq l_a^{-1}(\omega) \tag{4.25}$$

Remark 4.4.3 The robust stability margin induced by the IMC control design applies to plants which have the same number of unstable poles. In this sense, the robust stability margin result for IMC control is more restrictive than the corresponding result for H_∞ control design subject to coprime factor perturbations as given by Theorem 4.1.

Remark 4.4.4 In general, the IMC control is not applicable to unstable plants. Lee (1994) overcomes the problem of unstable plants by a two step iterative identification and control design, where, first, the unstable plant is stabilised by a parallel output feedback controller, and then the iterative paradigm is applied to the stabilised plant.

4.4.2 Identification

Another reason for chosing an IMC control design is that it induces a performance degradation,

$$\| \frac{CP}{1+CP} - \frac{C\hat{P}}{1+C\hat{P}} \|_{\infty}, \tag{4.26}$$

which can be approximately minimised by an L_2 identification of a plant model, $\hat{P}(\theta)$, which satsifies the criterion,

$$\theta^* = \arg\min_{\theta} \frac{1}{2\pi} \int_{-\pi}^{\pi} | \frac{(P - \hat{P}(\theta))C}{(1+CP)(1+C\hat{P})} |^2 d\omega. \tag{4.27}$$

As will be shown below, this control-relevant identification criterion corresponds to the indirect closed loop identification via the dual Youla-parametrization which was introduced in Section 3.5. Recall that with this method, the identified dual Youla-parameter, $\hat{R}$, is used to update the plant model, $\hat{P}$. A criterion, (3.37), associated with the identification of the dual Youla-parameter was given. This criterion only characterises the open loop identification of the dual Youla-parameter, $\hat{R}$. It does not provide a characterisation of the updated plant model. In order to show that the updated plant model resulting from an indirect closed loop identification using the dual Youla-parametrization conforms to the plant model which would have resulted from the minimisation of the performance degradation criterion, (4.27), the following result is required.

Lemma 4.3 *(Lee* et al, *1993a, 1993b). Let $\hat{P}_i = \frac{N_i}{D_i}$ be a coprime factorisation of a nominal plant model which is stabilised by the controller, $C = \frac{X}{Y}$. X, Y are the coprime factors of C. Let $\hat{R}$ be a dual Youla-parameter, which together with the nominal plant model, $\hat{P}_i$, and the controller, C, defines the set of all plants stabilised by the controller, C. A particular plant model, $\hat{P}_{i+1}$, in this set is given by :-*

$$\hat{P}_{i+1} = \frac{N_i + \hat{R}Y}{D_i - \hat{R}X}. \tag{4.28}$$

By choosing coprime factors,

$$N_i = \hat{P}_i; \quad D_i = 1, \tag{4.29}$$

$$X = \frac{C}{1+C\hat{P}_i}; \quad Y = \frac{1}{1+C\hat{P}_i}, \tag{4.30}$$

then $\hat{R}$ satisfies

$$\hat{R} = \frac{(\hat{P}_{i+1} - \hat{P}_i)(1 + C\hat{P}_{i+1})}{(1 + C\hat{P}_{i+1})} \tag{4.31}$$

Proof: See Appendix B. ■

Theorem 4.3 *(Lee* et al, *1993a, 1993b). Given the dual Youla-parameter, $\hat{R}$, as defined in Lemma 4.3, and a filtered output error equation,*

$$\xi(k) = (1 - \hat{T}(\hat{P}_i, C))(\beta(k) - \hat{R}\alpha(k)), \tag{4.32}$$

then $\xi(k)$ can be expressed as :-

$$\xi(k) = \frac{P - \hat{P}_{i+1}}{(1 + CP)(1 + C\hat{P}_{i+1})} r(k) + \frac{H}{1 + CP} e(k). \tag{4.33}$$

Proof: See Appendix B. ■

Hence, by injecting the excitation at the controller input rather than at the plant input, and by choosing a data filter, $D = 1 - \hat{T}$, the minimisation of a performance degradation criterion, (4.27) can be achieved using indirect closed loop identification via the dual Youla-parametrization. Of course, since the dual Youla-parameter, $\hat{R}$, must be estimated, the accuracy of this estimate will determine to what extent the plant model reflects one which minimises the performance degradation.

Due to the parametrization (4.28), the updated plant model will be of significantly larger order than the current nominal plant model (even with a low order estimate of the dual-Youla parameter, $\hat{R}$). Therefore, either model or controller reduction will be required to prevent the propagation of controller order with each identification.

4.4.3 Iterative Design

To sumarise, the distinguishing features of the Lee *et al* iterative approach are (Bitmead, 1993):-

- an IMC control design which is amenable to robustness analysis and hence the provision of a robust stability test prior to controller implementation.

- a single controller design parameter; the closed loop bandwidth, λ, which allows for cautious controller enhancements.
- infrequent control-relevant L_2 identification as the need arises.
- an explicit requirement for either model or controller reduction to prevent escalation of controller order.
- applicability only to stable or stabilised SISO systems.

4.5 Other Iterative Approaches

Åström (1993) considers an iterative design in which a least squares identification criterion is matched to an LQ control criterion through the selection of appropriate data filters. Conceptually this approach is similar to that of the Zangscheme.

Bayard *et al* (1992) propose a criterion for the joint optimisation of identification and robust control. An algorithm is proposed for solving the joint optimisation problem, based on alternating between curve fitting and control design steps. This theoretical strategy yields monotonically decreasing achieved controller performance. Unfortunately, at present there exists no direct optimisation methods to minimise the curve fitting and control design criteria. For these practical reasons, Bayard *et al* (1992) adopt a standard curve fitting algorithm to fit noiseless frequency response data to a plant model in a control-relevant manner. This model is then used in weighted mixed-sensitivity control design. This practical approach is similar to an early version of the Delft iterative design which used frequency response data in a control-relevant manner (Schrama, 1992a).

Remark 4.5.1 Frequency response data can be obtained through an open loop experiment, where a number of different discrete frequency sine-waves over the frqeuency range of interest are injected at the plant input. The frequency response of the plant at each discrete frequency can be determined by observing the magnitude and phase response of the output. Frequency domain identification is a non-parametric identification method (Ljung, 1987). This approach has been successfully applied to plants associated with aerospace industry or flexible structures, e.g. Crisafulli *et al* (1994a), Balas and Doyle (1990), Bayard *et al* (1989). Unfortunately, injection of sine-waves over many discrete frequencies is not practical for most process industry plants.

The iterative scheme of Liu and Skelton (1990) uses a q-Markov COVER approach to closed loop identification and an output variance constrained (OVC) controller for the control design. q-Markov COVER theory has been developed for describing COVariance Equivalent Realisations of multi-variable discrete time systems from finite length input-output data (King *et al*, 1988). Reduced order q-Markov COVERs can also be found. From a technical perspective the q-Markov COVER approach to iterative design is significantly different from the other expounded iterative schemes.

The Liu and Skelton (1988) closed loop identification experiment is a collection of impulse response tests conducted on the plant with the current controller operating. The impulse response parameters of a discrete time system are the Markov parameters. The closed loop impulse response parameters are used to construct a model of the closed loop. Using this closed loop model and knowledge of the controller, an open loop plant model is derived. q-Markov COVER model reduction is used to obtain a reduced order plant model.

The OVC controller minimises the control energy of the closed loop system subject to inequality constraints on the variance of each closed loop output. Both identification and control design in the q-Markov COVER iterative scheme are focussed to matching the second order (covariance) properties of the closed loop signals. The iterative design incorporates a convergence check on the designed controllers. If the difference between the current and previous controllers is within a certain tolerance, the iteration is stopped. Like the other iterative designs, controller convergence will depend upon the application.

Graebe *et al* (1993) and Graebe and Goodwin (1993) merge techniques of incremental estimation, stochastic embedding and internal model control (IMC) into an iterative identification and control design procedure. Like the IMC iterative scheme this scheme is cautious, the final closed loop bandwidth is approached incrementally. By embedding the model uncertainty as a stochastic process, the unknown unmodelled dynamics can be quantified. Consequently, it is possible to predict the expected achieved closed loop bandwidth. Explicit prediction of closed loop performance was also available in the Delft iterative scheme.

Kosut (1995) proposes an iterative approach in which a family of uncertainty models that cannot be falsified by the measured data is used to construct a family of robust controllers. The family of uncertainty models is parametrized by the model bandwidth and a dynamic uncertainty bounding parameter. For each model bandwidth/uncertainty setting, a controller is designed which achieves robust performance with respect to the corresponding uncertainty model. Each controller in the family of controllers is evaluated by implementing them on the actual system and monitoring performance as the model bandwidth parameter is slowly increased and the uncertainty parameter is slowly decreased. When the performance is worse than predicted, the uncertainty model is falsified, and the iterative scheme then returns to the model invalidation step where new data is used to unfalsify a new family of uncertainty models.

The iterative approach of Kosut (1995) employs model validation concepts of Smith and Doyle (1992) to connect identification and robust control. In addition, the scheme features a model bandwidth parameter used to falsify an uncertainty model. The closed loop bandwidth parameter of the IMC iterative scheme serves a similar purpose.

4.6 Chapter Conclusion

This chapter has presented a number of viable iterative identification and controller design which could be used to enhance controller performance. These scheme use finite length records of measured input-output data. As such, these schemes have potential utility for application in process industry where, typically, large amounts of process data are readily available.

This chapter concludes the review of the technical machinery necessary for controller refinement. It is evident from the weight of material presented so far, that the application of advanced control techniques, such as iterative identification and controller design, to industrial processes requires considerable technical knowledge in the areas of System Identification and Control theory. The large flag-fall to acquire these technical skills, not to mention experience in applying them, infers that the responsibilities of a control engineer practising advanced control are those of a specialist. Nevertheless, the advanced control solution for any industrial process must meet the requirements of the end-user. In the next chapter, the requirements of advanced control strategy for a sugar cane crushing mill are detailed.

Chapter 5

Sugar Cane Crushing Problem

5.1 Chapter Motivation

Crushing mill control in the sugar industry is beset by the need to regulate the process behaviour to maintain high performance in the face of marked feedstock variations. With sugar cane these variations are determined by the physical properties of the sugar cane which varies dramatically with plant variety, and the climatic and soil conditions experienced as the sugar cane crop is cultivated. The primary objective of the sugar milling process is to extract as much sugar bearing juice as possible from the cane at a reasonable throughput rate.

Conventional well-tuned PID control of the crushing process is sufficiently robust to cope with the feedstock variations, but at the expense of performance. Conservative set-points are chosen and the variation of the process outputs from set-point is high. Recent plant experiments have quantified that at least 2.4% of available sugar is not extracted by the crushing process during normal process operation (Peirce, 1994) under PID control. The application of advanced control to the crushing process offers the potential to recover some, not all, of the previously unextracted sugar. Based on the world market sugar price of 12.5 cents(US)/lb, successful application of advanced control to a crushing process could generate up to an additional \$500 (AUD) per eight hour shift in revenue (based on a foreign exchange rate 1AUD = \$0.75US). This amount renders the application of advanced control, financially attractive, justifying this investigation into controller refinement.

The application detailed in this thesis pertains to the A-side crushing process at CSR Ltd's Victoria Mill, Ingham, Queensland. Around 2.6 millions tonnes of harvested sugar cane from the Herbert River sugar cane growing region is sent to Victoria Mill for crushing. Victoria Mill holds the distinction of being the largest raw sugar factory in the southern hemisphere. The A-side milling train at Victoria Mill is a full-scale industrial crushing process which normally operates at throughput rate of 550 tonnes/hour. In spite of the similarity of these mills to others in use throughout the Australian sugar industry, these particular mills appear unusually uncontrollable and exhibit lengthy periods of poor extraction performance under PID control. These mills therefore stand to gain the most from any improvement in control performance.

5.2 The Sugar Cane Crushing Process

5.2.1 Process Description

The basic principle of extracting sugar from the sugar cane plant involves a simultaneous breaking of the cellular structure of the plant to release the sugar solution and a squeezing of the resultant fibrous mat to express the sugar juice. This typically is achieved by feeding the sugar cane fibre between large-diameter rolls powered by a steam turbine driving the rolls through a speed reducing gear train. Figure 5.1 shows the major components of a single milling unit. In practice a number of these units, generally from 3 to 6, operate serially to form a milling train. Usually, the first mill is controlled in such a manner as to set the consumption/throughput rate, with the remaining mills controlled to achieve high extraction. Maximum extraction of sugar juice from the sugar cane plant is one of the key objectives in maximising the profit of a raw sugar factory, and the milling train is therefore an important plant item. A key element in maximising extraction of sugar from the cane fibre is to maintain the torque applied to the crushing rolls close to a relatively high set-point. Experimental results given in Figure 5.2 confirm an empirical relationship between torque and extraction (Peirce, 1994). The solid line in Figure 5.2 represents mill operation at torque set-points of 1.0 MNm, whilst the dashed line is for operation at 0.8 MNm.

5.2.2 Process Variables

In considering the sugar cane crushing problem, the actual process variables of height, $\mathcal{H}_k$, torque, $\mathcal{T}_k$, speed, $\mathcal{S}_k$, and flap position, $\mathcal{F}_k$ are replaced by their deviations from set-point

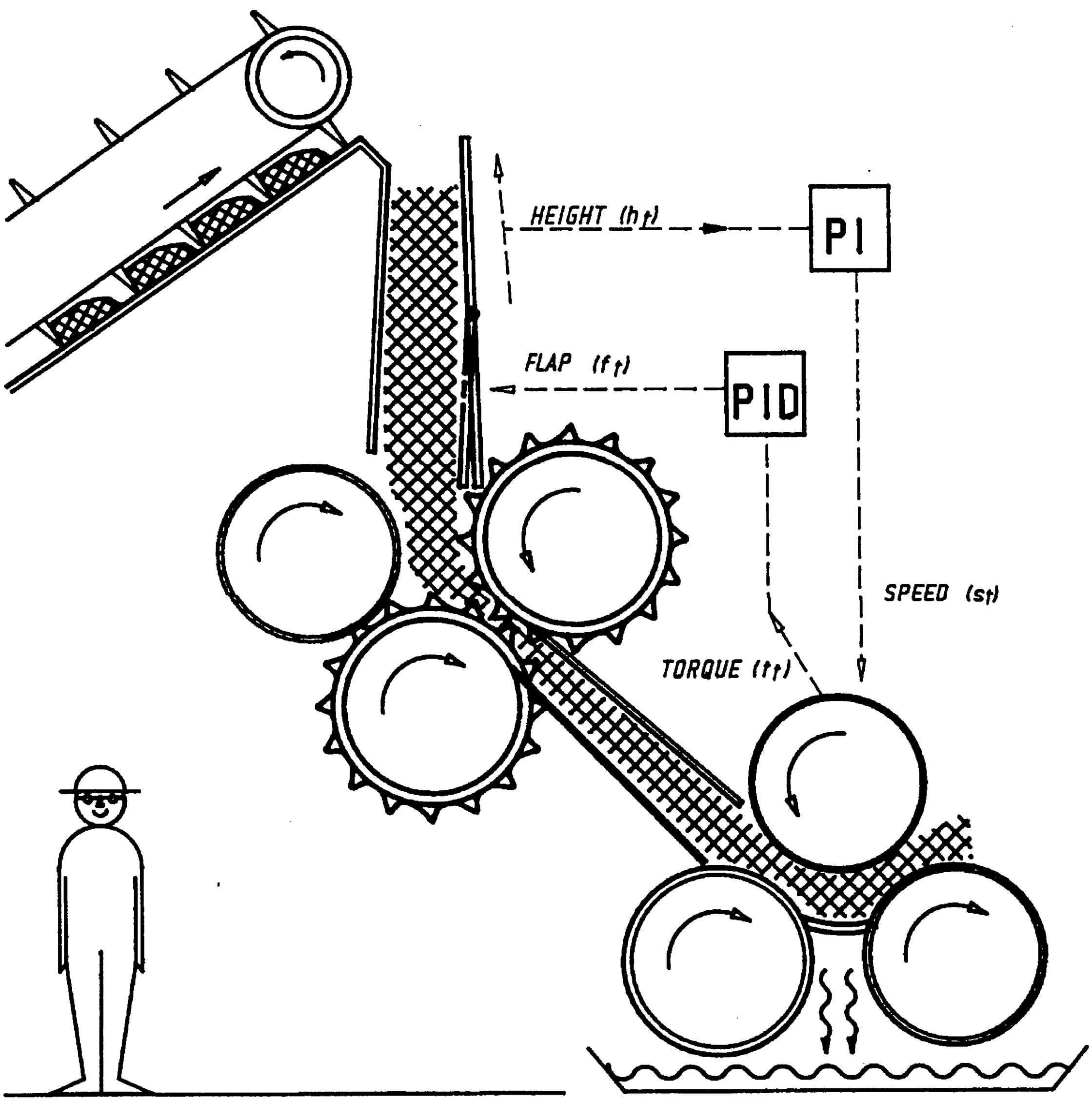

Figure 5.1: Diagram of sugar mill operation

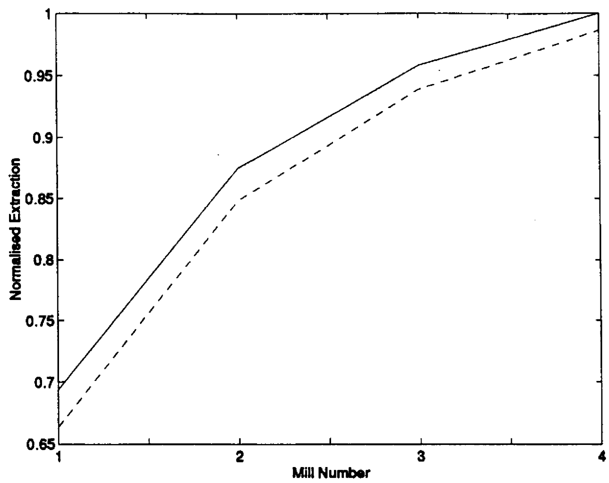

Figure 5.2: Normalised Extraction versus Mill Number for various torque set-points.

or nominal values, i.e.

$$\left.\begin{aligned} h_k &= \mathcal{H}_k - h^\star \\ t_k &= \mathcal{T}_k - t^\star \\ s_k &= \mathcal{S}_k - s^\star \\ f_k &= \mathcal{F}_k - f^\star. \end{aligned}\right\} \tag{5.1}$$

The process output signals are turbine torque, t_k, and chute height, h_k. The input controls are turbine governor speed signal, s_k, and the chute flap position actuator signal, f_k. Other, process variables such as turbine chest pressure, top milling roller lift, and maceration boot level, are also logged, although they are not used in the controller design. Since the sugar cane crushing process is a part of nearly all raw-sugar milling operations, for financial and maintenance reasons it is desirable to implement an advanced control solution which only utilises the currently measured process variables. This end-user requirement dictated that no additional instrumentation was to be added to the plant.

Remark 5.2.1 To maintain notational simplicity for the crushing process variables, the sample index, k, appears at subscript location rather than in parentheses after the variable, as was the case in Chapters 2-4.

5.2.3 Process Objective

The primary objective of the crushing process is to maximise extraction at a throughput rate which guarantees that an agreed harvest tonnage supplied by the district farmers can be processed by the miller during the allotted 22.5 week crushing season. Given the ubiquity of similar crushing processes throughout the Australian sugar industry, this objective is to be achieved without capital intensive modifications to the process. Hence, the adoption of a control solution to realise indirectly the original process objective. The control objective considered in this thesis seeks :-

> *to maximise extraction through better torque regulation during normal operation.*

A number of mechanisms exist to adjust the torque. Specifically, such mechanisms vary,

- the physical distances between the main crushing rolls. Nominally these distances are fixed, although in most cases the crushing rollers are hydraulically loaded permitting the rollers to lift causing the mill opening to widen should the pressure exerted by the bagasse[1] upon the crushing rollers exceed a preset limit. This action occurs during normal operation when the torques are sufficiently high.
- the outlet geometry of the vertical feed chute, thus allowing more or less fibre to pass to the crushing rolls. This is achieved by manipulating the relative position of a flap located at the front or at the back of the vertical feed chute, or both. For crushing units considered in this thesis the flap is located at the back of the feed chute. However, solely controlling the flap position does not constitute an effective control strategy since the operating range of the flap position is not sufficient to prevent the feed chute from, either overflowing or completely emptying. Usually, manipulation of the flap position is undertaken with a control action that adjusts the speed of the mill rolls to ensure that the feed chute constraints are not violated.
- the height of bagasse within the feed chute, thus affecting the degree of compaction of the fibre at the entry to the pressure feeder rollers. This is primarily achieved

[1] Within the sugar industry, sugar cane fibre which has passed through a crushing process is referred to as *bagasse*.

by manipulating the speed of the turbine driving the pressure feeder and crushing rollers. The relative position of the flap also influences the height of the bagasse within the chute.

For the purposes of controlling torque over a wide operating range, the last two mechanisms are viable.

Remark 5.2.2 Historically, crushing mills were controlled via the chute height-prime mover speed loop. Prior to the introduction of steam turbines this single-loop control was adequate for the low-throughput milling unit driven by a low-powered reciprocating steam engine. However, the advent of significantly higher power steam turbines required much better control of prime mover speed and of the torque which was sufficient to damage the mechanical components of the milling unit, in particular the low speed gear reducer unit which is at the upper level of gear design technology. This led to the introduction of the torque/chute flap position control loop which essentially acts as an over-ride on high torque values by choking the supply of bagasse to the mill rolls.

Remark 5.2.3 Poor control of the crushing process which is at the front-end of a raw sugar factory is known to propagate to other downstream factory processes and adversely affect their performances. Therefore, if one process control loop begins to behaves badly, other surrounding loops also perform poorly. This is a common problem in process industries which causes unnecessary high enery consumption, waste of raw material, and often results in large variations in the final product quality (Hägglund, 1994).

5.2.4 PID versus Multi-variable Control

Control and process variable interactions associated with the two viable control mechanisms for the sugar cane crushing process obviously imply that the process is multi-variable. Advanced control techniques such as multi-variable model-based controller synthesis and analysis methods are, in practice, difficult to apply. Therefore, although the process is multi-variable, the current PID control strategy implements a two-loop decentralised control, as shown in Figure 5.1. The decentralised control loops are the torque/flap position PID loop and the chute height/turbine speed PI loop.[2] These loops can easily

[2] Although the chute height/turbine speed controllers often include a small amount of derivative gain, the predominant control action is very much PI-like. Hence, the existing chute height/turbine speed controllers are classified as PI.

be tuned by plant engineers and plant electrical/instrumentation tradespersons using the Ziegler-Nichols tuning rules. Ziegler-Nichols rules cannot be easily modified for multi-variable processes. Technically, the application of multi-variable model-based controller methods is better suited for the multi-variable sugar cane crushing process than PID control, hence the emphasis on advanced control methods for controller refinement in this thesis.

5.2.5 Process Disturbances

Crushing process behaviour is affected by variations in the physical properties of the sugar cane plant, e.g. hardness, fibre length. These variations constitute a process disturbance, and are due to regional and seasonal factors and the selection of cane variety by farmers. Currently it is not possible to quantify accurately either the dynamical or statistical nature of this variation. However, the variation can be classified as consisting of :-

- short-term fluctuations, changing with periods of between a few, to many minutes, with sometimes quite large magnitude due to the many different types, or varieties, of cane grown in a particular district and the climatic and soil conditions under which the cane was grown.
- a longer period of change, superimposed on the short-term fluctuations, due to seasonal maturing of the sugar cane plant and wear and tear on the milling machinery.

In some instances the cane may be diseased or include large amounts of dirt (mud), further compounding the difficulty in predicting the nature of this variation (Partanen, 1994). It should also be noted that the milling characteristics of the sugar cane fibre are modified after each stage of crushing in a fashion which is usually detrimental to the extraction objective of the process. This is evidenced by the increasing difficulty of controlling the individual crushing units as one proceeds down the milling train.

The physical variations can be perceived by large deviations from set-point in torque and feed chute height. Torque deviations below set-point cause a loss of extraction resulting in a loss of profit. Large torque deviations above set-point place at risk of mechanical damage expensive plant machinery. In the extreme cases, large deviations in the feed chute height could cause the chute to fill or empty past its operational limits. The undesirable consequences of violating the feed chute constraints are :-

- production downtime as overflows will eventually cause a choke in the delivery system and prevent the flow of material.

- gaps associated with chute emptying which will initially upset the downstream crushing processes and subsequently undermine the performance of other major factory processes.

Given the large fluctuations in the physical properties of the sugar cane, resultant violation of the feed chute constraints is a common occurence.

Remark 5.2.4 Gross variations in the feedstock are not a problem specific to the sugar industry. For example, other process industries experiencing similar problems include metal and mineral processing (Sommer, 1992, Sommer *et al*, 1992, Mills *et al*, 1991, Lynch *et al*, 1981), paper (Dumont, 1990, 1986, Åström, 1967), cement (van Breusegem *et al*, 1994), glass (Wertz *et al*, 1992, Wertz and Demeuse, 1987), chemical (Seborg, 1986).

5.3 Controller Design Considerations

5.3.1 Candidate Control Strategies

The mechanisms available to manipulate the torque can be effected by a number of different feedback control strategies. The strategies include :-

1. regulation of the chute height about a high set-point to assist feeding by compaction in the vertical chute, thereby aiding the development of torques exerted by the crushing rolls. The chute height regulation control objective can be realised with a regulation criterion of the form,

$$\lim_{N\to\infty} \frac{1}{N} E\left[\sum_{k=1}^{N} h_k^T h_k + \lambda s_k^T s_k\right], \tag{5.2}$$

   where λ penalises the degree of control action possible by manipulating the turbine speed.

2. regulation of the turbine torque by manipulating the speed of the mill rolls without violating the constraints imposed by the empty and full limits of the feed chute. The

regulation criterion corresponding to this control strategy is,

$$\lim_{N\to\infty} \frac{1}{N} E\left[\sum_{k=1}^{N} (\,\sqrt{\epsilon}h_k^T \quad t_k^T\,) \begin{pmatrix} \sqrt{\epsilon}h_k \\ t_k \end{pmatrix} + \lambda s_k^T s_k\right], \tag{5.3}$$

$$= \lim_{N\to\infty} \frac{1}{N} E\left[\sum_{k=1}^{N} \epsilon h_k^T h_k + t_k^T t_k + \lambda s_k^T s_k\right], \tag{5.4}$$

where ϵ is the weighting which trades torque control for chute height control when the chute height is far from set-point.

Remark 5.3.1 The above candidate control strategies are formulated in a manner congruent with the process objective of high extraction which is linked to maintaining turbine torques at sufficiently high levels. Hindsight after trialling the first candidate strategy of height regulation indicates that the feed chute ought to play a role primarily as a buffer, with the regulation of the chute height about very high set-points not being particularly critical to achieving high torques. Hence, torque regulation is the preferred control strategy.

Remark 5.3.2 Note, that the method proposed for torque regulation is not supported by traditional milling theory (Murry and Holt, 1967). In Section 5.3.2 it was stated that the flap position can be used to manipulate the torque. During closed loop operation the flap affects the torque indirectly via the interaction between the turbine speed and the chute height. Hence, the proposed torque regulation strategy has been formulated to use the turbine speed as the manipulated variable.

Remark 5.3.3 The height regulation strategy results in the design of a one-input one-output (1i1o) or SISO controller, whereas a two-input one-output (2i1o) controller is necessary for torque regulation.

Remark 5.3.4 Two-input two-output (2i2o) multi-variable controllers were also trialled. However, the inordinate number of control design design variables and the difficulty in selecting appropriate values hindered the successful implementation of the multivariable designs. For this practical reason, multi-input multi-output (MIMO) controller design was not pursued on the A-side crushing process at CSR Ltd's Victoria mill.

5.3.2 Robust versus Adaptive Control

A robust control solution was preferred to a traditional adaptive control solution. With a robust control design, the aim is to obtain a feedback controller which has the capacity to perform well with most cane varieties without too much compromise in performance. With traditional adaptive control, the milling properties of the sugar cane must be estimated on-line, using measurable process variables. Estimation of these disturbance properties is difficult. The problem is compounded by the non-uniformity of the physical properties of the sugar cane for a given variety. Recent success with preliminary investigations into the on-line estimation of the cane fibre rate (Crisafulli *et al*, 1994c) indicates the potential viability of applying similar estimation techniques to obtain a representative estimate of the milling properties of the sugar cane. However, the quantity of research and development to realise such an estimate and then to incorporate successfully its use into a control scheme is considerable. A robust control approach utilising *a priori* knowledge of the qualitative behaviour of the disturbances associated with milling properties offers an immediate solution. Controller refinement can then be undertaken using *a posteriori* information to enhance performance. As explained in Section 2.4, the utility of *a posteriori* knowledge adds an adaptive agenda to robust control. This does not necessarily mean that the control law is continuously adapted, as is the case with traditional adaptive control.

5.3.3 LQG Control

Both of the above control strategies can be realised using a model-based LQG time-invariant control design (Åström and Wittenmark, 1990). With LQG control design, a feedback control law results from the optimisation of a performance criterion given a linear model of the process behaviour. For complex industrial processes like the sugar cane crushing mill, linear controllers are, at best, a crude approximation to the unobtainable optimal control solution. Nevertheless, LQG controller design for the sugar cane crushing process can be justified for the following reasons :-

- for many crushing mills the process behaviour is essentially linear for much of the operating range. Nonlinearities associated with the process constraints can be managed to some degree by including a nonlinear addendum to the control law. Nonlinearities due to fluid pressures within the bagasse blanket are considerably more problematic since they are not yet well-understood and, therefore they cannot easily be accommodated in the final control law.

- the performance criterion to be optimised can be easily written in terms of the process input-output signals.

- the controller design can be relatively easily and fairly reliably performed using the available software packages (Grace *et al*, 1992). In the author's opinion, the acquistion of a reliable nonlinear control solution is considerably more problematic.

- a range of user selectable design parameters can be incorporated into the controller design. This provides the designer with an off-line mechanism to tune the controller response.

- the control law can be easily implemented on the available factory computing platform. This is not necessarily the case with nonlinear control designs.

- the modelling phase can be manipulated to produce a model specifically suited to the intended control design (Van den Hof and Schrama, 1994, Gevers, 1993).

- LQG control can be implemented with Loop Transfer Recovery (LTR) to recruit robust stability (Bitmead *et al*, 1990).

- LQG control theory has connections with Generalised Predictive Control (GPC) (Clarke *et al*, 1987a, 1987b) – a model-based control design procedure which has achieved some success in the process industries (Bitmead *et al*, 1990). Recent theoretical developments have seen the extension of GPC techniques to incorporate process constraints and nonlinearities (Clarke, 1994).

- an available iterative model identification and control design methodolgy using LQG can be used to improve the performance of the current LQG controller (Zang *et al*, 1995, 1992, 1991). This iterative paradigm is the Zangscheme presented in Section 4.2.

- in a new direct controller design using stochastic gradient methods (Ljung and Söderström, 1983), an LQG performance criterion is minimised by directly adjusting the existing controller parameters (Hjalmarsson *et al*, 1995, 1994b, 1994c). The advantage of direct controller designs is that no model of the process behaviour is required.

- the control designs does not require an estimate of model uncertainty. Therefore, model uncertainty estimation does not need to be conducted. As explained in Section 2.6, model uncertainty estimation techniques and implementation software for these methods have not yet reached maturity, and therefore were not considered sufficiently reliable for application to a full-scale production process.

5.3.4 Iterative Identification and Control Design

The sugar cane crushing process is a multi-variable process with unknown parameters. As has already been motivated in Section 2.7, iterative identification and control design provides a mechanism by which to enhance gradually controller performance for unknown systems.

The sugar cane crushing process possesses four generic attributes which permit the application of the Zangscheme signal-based iterative identification and controller design methodology, namely :-

- that it is applicable to multi-variable systems,
- the quantity of closed loop input-output data is generous and experiments may be conducted,
- the identification must be performed in closed loop as the crushing process effectively contains integral action and as such is asymptotically unstable, and
- it involves a process which is difficult to model via low order linear time-invariant systems, and is difficult to control given that an accurate dynamical process description does not exist.

In addition, the Zangscheme employs LQG controllers, the utility of which has been justified in Section 5.3.3 for controlling the sugar cane crushing process.

With the Zangscheme the order of the identified models is fixed by the user, consequently the controller order is constrained by the use of the certainty equivalence principle and LQG controller design. This is not necessarily the case with competing approaches such as IMC iterative design and earlier versions of the Delft iterative design which employ the dual-Youla method of closed loop identification. In these iterative schemes, the updated plant model estimate is parametrized in terms of the existing controller, an initial plant model, and an estimated dual-Youla parameter. Therefore, the updated plant model order is generally much larger than that of the initial plant model. Hence, model and/or controller reduction becomes necessary in these iterative designs to obtain a restricted complexity controller. With the Zangscheme controller reduction may be required for a multi-variable design, since the large number of frequency weightings will reflected by a high order frequency weighted LQG controller. For the sugar cane crushing process, a maximum of six orders is available for controller implementation on the current factory computers (Partanen *et al*, 1994).

Remark 5.3.5 The use of other iterative designs suitable for multi-variable sugar cane crushing processes could also be contemplated. For a wide class of plants, the superiority of one iterative scheme over another is far from clear. In this application, the choice of a control design criterion which is aligned to the process objective is the primary motivation behind the use of the Zangscheme iterative design, recall Remark 2.3.1.

The LQ control criterion, (5.4), can be modified into a frequency-weighted version,

$$\lim_{N\to\infty} \frac{1}{N} E\left[\sum_{k=1}^{N} \epsilon(F_1^h h_k)^2 + (F_1^t t_k)^2 + \lambda(F_2 s_k)^2\right], \tag{5.5}$$

where,

$$(F_1^h)^2 = \frac{\Phi_h(\omega)}{\Phi_h^c(\omega)}; (F_1^t)^2 = \frac{\Phi_t(\omega)}{\Phi_t^c(\omega)}; (F_2)^2 = \frac{\Phi_s(\omega)}{\Phi_s^c(\omega)}. \tag{5.6}$$

Remark 5.3.6 Third order auto-regressive (AR) models are used to approximate the numerator and denominator of $\Phi_h^{\frac{1}{2}}, \Phi_{h^c}^{\frac{1}{2}}$, etc.

Remark 5.3.7 The achieved closed loop signals, s_k, h_k, t_k, are all measurable and hence their spectra are readily identifiable.

Remark 5.3.8 The measured flap position, f_k, is treated as a known disturbance in the designed closed loop, and other designed closed loop signals, s_k^c, h_k^c, t_k^c, are readily computable.

Remark 5.3.9 The individual frequency weightings, F_1^h, F_1^t, F_2, associated with the multivariable crushing process, unlike the SISO case of Section 4.2, are not equal.

Remark 5.3.10 Gaps in the supply of feed material to the crushing mill as well as production stoppages necessitate that the feedback controller is stable. Equally, by open loop simulation it is desirable to check the sensibility of the controllers as a comparison to the existing control. Open loop stable controllers are a requirement for many process industry control systems. The frequency-weighted LQG controller design guarantees a feedback controller which is capable of stabilising the designed closed loop system. However, it does not guarantee an open loop stable controller.

Remark 5.3.11 Three third order frequency weightings add an additional nine orders to the existing LQG controllers. Sixth order is the maximum allowable controller order in the sugar mill's distributed computing environment. Therefore controller reduction is necessary prior to controller implementation. Balanced truncation controller reduction techniques in the MATLAB Control Systems Toolbox (Grace *et*, 1992) require that the full order controller's state transition matrix is stable (all eigenvalues inside the unit disc). This reinforces the need for an open loop stable controller.

To summarise, the Zangscheme iterative identification and controller design scheme consists of two stages, namely,

- a model adjustment stage where closed loop identification is performed using closed loop input/output signals obtained from an identification experiment in which the current controller operates on the plant with excitation injected. Identification design variable selection is related to robustness requirements.
- a controller enhancement stage where a frequency-weighted LQG controller design is undertaken using the identified plant model from the model adjustment phase and with frequency weightings obtained from closed loop input-output signals.

Chapter 7 will feature several possible variants to the Zangscheme which result from considering different orderings in the identification and control design stage.

5.3.5 Process Model Identification

The Zangscheme iterative design for controller refinement is a model-based methodology. As such, the Zangscheme requires an adequate model of the process, consisting of a dynamical process and a model for the disturbance. An accurate dynamical description of the sugar cane crushing process does not exist. Like many industrial processes, the complex interactions associated with the physics of this process are not well understood. Under these circumstances, a black box model can be fitted to experimental input-output data using System Identification (Ljung, 1987). A disturbance model can be formulated using *a priori* knowledge gained through process observations.

Without feedback control, continuous operation of the crushing process is not feasible as the crushing process is unstable. Therefore, the identification of a process model must be undertaken using closed loop input-output data. Closed loop identification can either be performed in a direct or indirect manner, recall Chapter 3. Regardless of the identification technique employed, two of the most important design variables available to the user to influence the outcome of closed loop identification are :-

- the spectrum of the excitation signal injected during the identification experiment.
- the frequency weighting used during the model fit. Usually this frequency weighting is effected by prefiltering the input-output data prior to performing the model fit.

Specific choices for the excitation spectrum and prefiltering can result in a model which is control-relevant. That is, an identification in which the interplay between identification and control design is taken into account. Identification design variable selection is examined further in Chapter 6.

5.3.6 Controller Maintainability

Despite the financial incentive to design and implement advanced controllers, this approach is not without its pitfalls. Today, there still exists a considerable gap between the theory and the practice of advanced control. It has been pointed in the conclusion to Chapter 4, that the practice of advanced control requires specialised expertise. In general, Australian process industries do not employ specialist control engineers, perhaps due to the dearth of good control engineers capable of accessing the potential benefits of advanced control. It could also be argued that lack of industrial employment opportunities for specialist control engineers may also be a reflection of their numbers.

To ensure, in the current climate of industrial practice with respect to advanced control, the continued successful deployment of advanced controllers, factory personnel must be able to update these controllers. In Australia, this is particularly the case, since many industrial sites are located in remote and/or rural districts which have considerable difficulty in recruiting from the small number of available engineers who possess advanced control design experience and expertise. As such, the maintenance of advanced control schemes is often left to factory personnel not sufficiently qualified or experienced with this technology. The result is that once the controller fails to deliver acceptable performance, usually following some process modification, it is taken off-line, and without outside assistance will, in general, remain off-line.

Although advanced control solutions have been successfully implemented at CSR Ltd's Victoria Mill, it is only at the process control engineer level that there exists some expertise internal to CSR Ltd to maintain these advanced control schemes. During the evolution of an advanced control solution for this process, many fundamental research problems needed to be solved due to the width of the theory-practice gap. Consequently, the technical details of the solutions may not be readily understood even at the engineer level, let alone at the tradesperson level.

To be able to derive the benefits of advanced controls, a considerable and continuous commitment to research and development, software engineering, maintenance, documentation, and the ongoing training of factory personnel is required.

5.3.7 Controller Implementation Platform

The sophistication of mill control systems has increased steadily, from the original simple mechanical, to electronic analogue, to the current microprocessor based systems. The presence of a modern distributed control system allows advanced control to be relatively easily applied to the selected plant items. A general purpose computer was interfaced to the plant via a dedicated communications interface and the distributed control systems input/output subsystem. All data logging and control actions are performed in the general purpose computer while the distributed control system is used to provide backup PID control, bumpless transfer between PID and LQG control, and the necessary operator interfaces. The distributed control system also provides the startup sequencing, event and alarm reporting, fault detection and emergency shutdown sequencing. Any control system, PID or advanced control, must be incorporated into the sequencing control system for the overall factory. System identification and controller design are performed in another

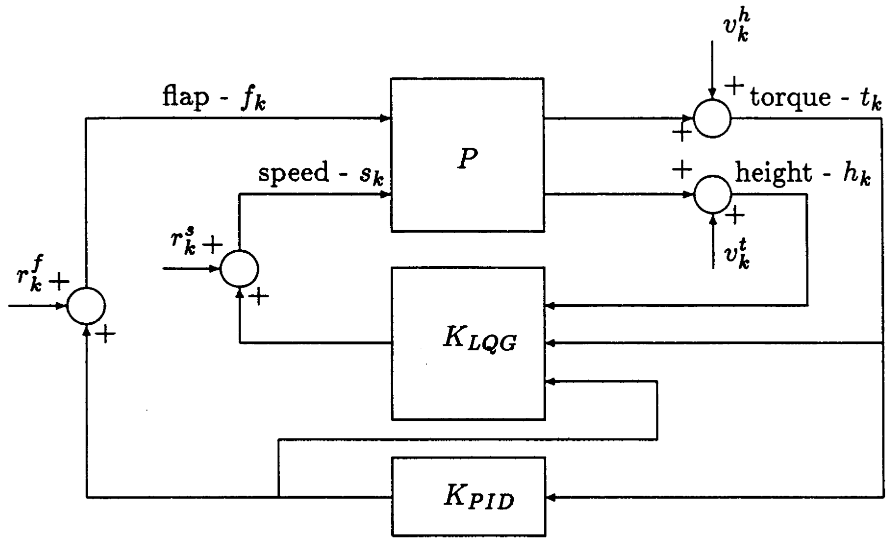

Figure 5.3: Feedback Control System for the Sugar Cane Crushing Mill.

general purpose computer networked to the one performing datalogging and control.

5.4 LQG Control Solution

This section details the LQG control solution for the preferred torque control strategy. This strategy seeks to minimise torque deviations about a high torque set-point by manipulating the turbine speed, provided the chute height has not deviated too far from its set-point. As the chute height moves further away from its set-point, the turbine speed is weighted in favour of controlling the chute height rather than the torque. This control strategy treats the flap position generated by the slow override torque-flap position PID control loop as a measurable disturbance input. The connection of the 2i1o torque controller with respect to the plant and override PID controller is given in Figure 5.3. In Figure 5.3, r_k^f and r_k^s are the external excitation signals added to the plant inputs of speed and flap during closed loop identification experiments.

5.4.1 Process Model

The multi-variable sugar cane crushing process may be approximated as a two-input two-output (2i2o) plant of the form,

$$\begin{pmatrix} h_k \\ t_k \end{pmatrix} = \begin{pmatrix} P_{hs} & P_{hf} \\ P_{ts} & P_{tf} \end{pmatrix} \begin{pmatrix} s_k \\ f_k \end{pmatrix} + \begin{pmatrix} v_k^h \\ v_k^t \end{pmatrix}, \tag{5.7}$$

where,

P_{yu} is the transfer function relating the input signal u, where u is either the turbine speed, s, or the flap position, f, to the output signal y, where y is either the chute height, h, or the turbine torque, t.

v_k^h is the additive output disturbance signal for the height model,

v_k^t is the additive output disturbance signal for the torque model.

Remark 5.4.1 The actual mill torque is not measured, however a calculated version of the turbine torque signal gives a good approximation. The turbine torque is readily computable from the turbine speed and the turbine chest pressure, given the manufacturer's turbine characteristics. Of course, direct measurement of mill torque would be preferable, however, as stated previously, end-user requirements prevent the addition of extra instrumentation.

Remark 5.4.2 The height and torque model additive output disturbances are considered to be adequately modelled by rational linear transfer functions driven by zero mean white noise processes with unit variance.

Remark 5.4.3 The identification of a 2i2o plant model consists of aggregating the 2i1o height and torque models which can be identified using prediction errors routines available in the MATLAB System Identification Toolbox (Ljung, 1991). Currently, it is not possible with the MATLAB System Identification Toolbox to identify MIMO models.

Remark 5.4.4 During the identification a disturbance model is estimated. This disturbance model contains not only disturbance information, it also contains manifestations of the effects such as process non-linearities, signal quantization, etc, which cannot be captured by the plant model (Bitmead *et al*, 1994). Consequently, for the control design, the identified disturbance model is replaced by a fixed model based on process knowledge of the dynamical effects of the changing cane variety. This *a priori* knowledge indicates that,

- the disturbance acting on the chute height is ramp-like.
- the disturbance acting on the turbine torque is step-like.

Hence the modelled disturbance signals, v_k^h and v_k^t, used during the controller enhancement phase possess known spectra.

5.4.2 Model Aggregration

From the two 2-input 1-output models, written in state-space form, and incorporating process noise and measurement noise terms,

$$\begin{aligned} x_{k+1}^h &= F^h x_k^h + \begin{pmatrix} G^{hs} & G^{hf} \end{pmatrix} \begin{pmatrix} s_k \\ f_k \end{pmatrix} \\ &+ \begin{pmatrix} G^{hs} & G^{hf} \end{pmatrix} \begin{pmatrix} w_k^s \\ w_k^f \end{pmatrix} && (5.8) \\ h_t &= H^h x_k^h + v_k^h && (5.9) \\ x_{t+1}^t &= F^t x_t^t + \begin{pmatrix} G^{ts} & G^{tf} \end{pmatrix} \begin{pmatrix} s_k \\ f_k \end{pmatrix} \\ &+ \begin{pmatrix} G^{ts} & G^{tf} \end{pmatrix} \begin{pmatrix} w_k^s \\ w_k^f \end{pmatrix} && (5.10) \\ t_k &= H^t x_k^t + v_k^t, && (5.11) \end{aligned}$$

plus the ramp-like and step-like disturbance models for the height disturbance, v_k^h, and the torque disturbance, v_k^t,

$$\begin{aligned} x_{k+1}^d &= F^d x_k^d + G^d w_k^d && (5.12) \\ \begin{pmatrix} v_k^h \\ v_k^t \end{pmatrix} &= H^d x_k^d + \begin{pmatrix} n_k^h \\ n_k^t \end{pmatrix}, && (5.13) \end{aligned}$$

where these noise matrices are given by (with disturbance pole at α),

$$F^d = \begin{pmatrix} \alpha & 1-\alpha \\ 0 & \alpha \end{pmatrix} \qquad (5.14)$$

$$\begin{aligned} G^d &= \begin{pmatrix} 1-\alpha & 0 \\ 0 & 1-\alpha \end{pmatrix} && (5.15) \\ H^d &= \begin{pmatrix} hramp & hstep \\ 0 & tstep \end{pmatrix} && (5.16) \\ w_t^d &= \begin{pmatrix} w_t^{d1} \\ w_t^{d2} \end{pmatrix}, && (5.17) \end{aligned}$$

one may compose an aggregated state model for the process plus disturbances in the form

$$\begin{pmatrix} x_{k+1}^h \\ x_{k+1}^t \\ \begin{pmatrix} z_{k+1}^h \\ z_{k+1}^t \end{pmatrix} \end{pmatrix} = \begin{pmatrix} F^h & 0 & 0 \\ 0 & F^t & 0 \\ 0 & 0 & \left(F^d\right) \end{pmatrix} \begin{pmatrix} x_k^h \\ x_k^t \\ \begin{pmatrix} z_k^h \\ z_k^t \end{pmatrix} \end{pmatrix} + \begin{pmatrix} G^{hs} & G^{hf} \\ G^{ts} & G^{tf} \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} s_k \\ f_k \end{pmatrix} + \begin{pmatrix} G^{hs} & G^{hf} & 0 & 0 \\ G^{ts} & G^{tf} & 0 & 0 \\ 0 & 0 & 1-\alpha & 0 \\ 0 & 0 & 0 & 1-\alpha \end{pmatrix} \begin{pmatrix} w_k^s \\ w_k^f \\ w_k^{d1} \\ w_k^{d2} \end{pmatrix} \tag{5.18}$$

$$\begin{pmatrix} h_k \\ t_k \end{pmatrix} = \begin{pmatrix} H^h & 0 & hramp & hstep \\ 0 & H^t & 0 & tstep \end{pmatrix} \begin{pmatrix} x_k^h \\ x_k^t \\ \begin{pmatrix} z_k^h \\ z_k^t \end{pmatrix} \end{pmatrix} + \begin{pmatrix} n_k^h \\ n_k^t \end{pmatrix}. \tag{5.19}$$

Given an aggegrated plant model in state space form, an LQG/LTR controller can be formulated for the preferred control strategy of torque regulation.

5.4.3 The LQG/LTR Torque Controller

By associating the disturbance processes, v_k^h and v_k^t, with the cane variety induced effects on milling performance, it is apparent that to achieve high control performance, the effect of the disturbances on the crushing process must be rejected. By rewriting the state and observation equations, (5.18) and (5.19), respectively, with a single state and making the appropriate assignments, the composite system,

$$x_{k+1} = Fx_k + Gs_k + Bf_k + Ww_k, \tag{5.20}$$

$$y_k = Hx_k + n_k, \tag{5.21}$$

is obtained. A discrete LQG/LTR control strategy applied to this system includes :-

1. an LQ optimal control problem on (5.20) with a criterion function,

$$J = \lim_{N\to\infty} E\frac{1}{N}\sum_{i=1}^{N} x_i^T Q_c x_i + u_i^T R_c u_i,$$

   where $Q_c = H^T H$, i.e. the objective function measures the weighted mean squared value of the output and the input, and $R_c = \lambda I$ with λ chosen as small as feasible.

2. a Kalman Filtering problem for state estimation with the process noise covariance $Q_o = GG^T$ and measurement noise variance R_o unconstrained, i.e. the process noise is modelled as entering the plant through the input channel.

This strict LQG/LTR design was altered by replacing the Kalman Filter above by the Kalman Predictor to permit a control law without direct feedthrough. The particular assignments for the LQ design were,

$$Q_c = \begin{pmatrix} \epsilon H^{hT} H^h & 0 & 0 \\ 0 & H^{tT} H^t & 0 \\ 0 & 0 & 0 \end{pmatrix}, \tag{5.22}$$

(observe that the disturbance states are uncontrollable and so do not enter the LQ criterion) and R_c a positive scalar, λ, weighting the cost of speed variations. Note, that this choice of design variables, Q_c, R_c, realises the regulation criterion, (5.4). This LQ design yields a state feedback gain, K. For the state estimator design R_o was chosen as ρI_2, where ρ is a positive design parameter, and

$$Q_o = GG^T, \tag{5.23}$$

where

$$G = \begin{pmatrix} G^{hs} & 0 \\ G^{ts} & 0 \\ 0 & \begin{pmatrix} 1-\alpha & 0 \\ 0 & 1-\alpha \end{pmatrix} \end{pmatrix},$$

yielding an estimator gain vector L.

The controller state variable realisation is then available as

$$x^c_{k+1} = [F - GK - LH]\, x^c_k + L \begin{pmatrix} h_k \\ t_k \end{pmatrix} + Bf_k, \tag{5.24}$$

$$s_k = -Kx^c_k, \tag{5.25}$$

where

$$G = \begin{pmatrix} G^{hs} \\ G^{ts} \\ 0 \\ 0 \end{pmatrix}, \quad B = \begin{pmatrix} G^{hf} \\ G^{tf} \\ 0 \\ 0 \end{pmatrix}.$$

Note the appearance of the flap position, f_k, as a measurable disturbance to the controller.

The formulation of a 1i1o LQG/LTR height controller, although less complicated than the 2i1o torque controller, is nevertheless very similar. The frequency weighted LQG solution also utilises the above formulation, however frequency transformations are required to solve the control design problem using standard LQG methods. For details of the frequency weighted LQG control design, the interested reader is referred to Appendix C.

In order to implement the LQG controllers of the Zangscheme iterative design successfully, a number of implementation issues which impinge upon the controller construction are resolved in the next section.

5.5 Implementation Issues

This section details an implementation of model-based LQG controllers on a factory computing platform, and some associated pitfalls. For successful implementation of model-based controllers it is imperative that the plant input-output data used during the controller design accurately represent the process. Similarly, issues arise concerning the physical and computational constraints on the controller. In the sugar cane crushing process application, the overall control and sequencing of the crushing station is scheduled by a Bailey Network90 (N90) Distributed Control System (DCS). Easy selection of PID or LQG control of the crushing mills was available to the plant operator. It was found that operator acceptance of a particular LQG controller determined its lifetime.

5.5.1 Data Integrity

Field Instrumentation

At the start of this project, the field transducers and actuators were calibrated to ensure that their electrical signals accurately represent the process variables. For some of the crushing process variables, the interface between the plant and its electrical representation at the field input-output terminals of the N90 is further complicated by an intermediate stage of electrical current to air-pressure conversion. Existing dashpots and snubbers in the air circuit tend to low-pass filter the information content of the mill process variables. To avoid this distortion, these dashpots and snubbers were either adjusted to have minimal effect or completely removed from the circuit. The control output to the turbine governor is one example where dashpots and snubbers caused delays in the response of the turbine; hence these were removed.

Given that the electrical signals at the field input/output (I/O) terminals of the N90 are representative of the process (due to our previous efforts of calibration), data logging of these signals provides a mechanism for checking the N90 numerical representation of these signals.

Quantization Effects

The height of bagasse in the chute is measured by 16 height probes mounted on the side of the chute. The chute height transducer produces a 16 level quantized electrical output which represents 0-100% of the chute height. The relative pulse width at a particular quantized level gives a measure of the bagasse height within the chute between probes. This quantized input signal is conditioned by hardware filters on the analog input card of the N90. This representation of the chute height was found to be sufficiently accurate for control purposes.

Signal Filtering

Further filtering of the field input-output signals by the N90 will occur onboard the N90 analog input-output cards, and possibly in the software function block program of the N90. Moving average and rate limiting function blocks distort the information content of the crushing mill process variables within the N90. Therefore only *raw* N90 data signals were logged for use during the system identification, control design and implementations. The term *raw* refers to those signals which have not been filtered in the N90 function block program. It should be noted that these *raw* signals are still conditioned by hardware filters of the N90 analog input-output cards. Usually this signal conditioning includes the filtering to remove very high frequency noise, and to protect the electronic cards from destructive effects of overvoltages. By identifying models using N90 signals, the filter and conditioners are incorporated into to the plant input-output model.

Data Sampling

The I/O data sampling rate for the milling process was chosen to be 1 Hz. Musumeci (1990) concluded that a sampling frequency of 1 Hz was sufficient to capture the spectrum of these signals. Faster sampling would have been computationally more demanding, and would have not provided significantly more information. Fast sampling may also falsely accentuate the importance of high frequency dynamics to the detriment of closed loop control (Crisafulli *et al*, 1994c).

Data Transfer

For the successful implementation of model-based control algorithms, the sampling of plant input-output data must occur continually at the required sampling frequency. In order to address this factor, the Victoria Mill's factory computing environment as shown in Figure 5.4 must be considered.

Crushing station field instrumentation is directly wired into a Bailey N90 DCS. The N90 DCS consists of process control units (PCU) and operator interface units (OIU) in the form of PCVIEW operator terminals. The transfer of crushing station I/O signals between the N90 and minicomputers on the mill office Ethernet local area network must occur continuously at the required sampling rate. Two methods of data communication between the N90 DCS and minicomputers on the office LAN are available:

1. Data transfers based on exception reporting to the Bailey N90 proprietary Industrial Local Area Network (ILAN) termed the *plant loop*. The *plant loop* is implemented as a ring topology network.

2. The addition of multi-tasking computing capability to the crushing station PCU to transfer data via an RS232 serial line.

The limitations of data transfers based on N90 exception reporting are:

1. Exception reporting only transmits signals along the plant loop once signal variation has exceeded a preset deadband.

2. The N90 has system override that limits the number of transmissions that a particular signal can make to the plant loop in a given time. In addition, traffic to the operator station has priority on the plant loop.

3. As other nodes are added to the N90 plant loop, the amount of network traffic on this ILAN increases.

These limitations may result in the distortion of the sampling frequency for the collection of crushing station input-output data.

To overcome the limitations of exception reporting on the plant loop, a dedicated RS232 serial communications link between the N90 DCS and the mill office local area network (LAN) was established for transfer of crushing station I/O data.

Again, logged electrical signals at the field input-output terminals of the N90 were used to verify the integrity of crushing plant data available on the mill office LAN.

5.5.2 Controller Implementation

Gaps, Windup and Nonlinear Gains

It is common for gaps to occur in the delivery of bagasse to a mill because of upstream problems. In these circumstances, the mill feed chute will run empty and the torque will drop. The tendency of the linear controller is then to slow the mill down continually until theoretically the chute fills and the torque rises. Naturally, the chute bottoms out at 0% full and the turbine is incapable of rotating in reverse. In such a circumstance, the chute height and torque deviations from set point remain strongly negative for an appreciable

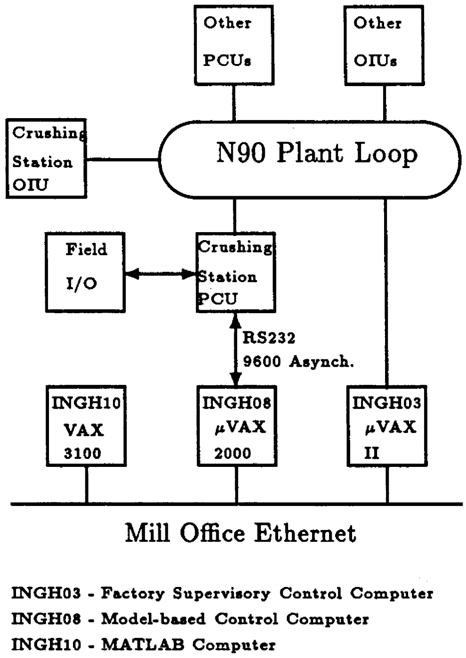

Figure 5.4: Factory Computing Environment.

time and do not respond to control actions. This is interpreted by the controller as exceptionally large negative ramp and step disturbances to the height and torque respectively. Any recovery from this state will take time for the input measurement to overcome this assessment. During this time the control system will fail to respond sufficiently rapidly to a resumption of flow of bagasse. An alternative explanation for this phenomenon is that the integral action in the controller, due to the disturbance model, 'winds up' or integrates this long negative signal and then takes a similar time to recover. As the chute can fill in around 20 seconds after a gap, the controller must be able to respond to the rapid rise in chute height after a gap to avoid chute overflows.

The relative degree of integral windup during a gap is reflected in a corresponding slow controller response after the gap clears. There are several mechanisms to deal with integral windup. Those which were applied to the sugar mill were,

- to replace the exact integrator in the disturbance models by low pass filters with poles slightly inside the unit circle, and
- a smooth nonlinear weighting to reduce the perceived magnitude of the height offset for chute heights of less than 30%.

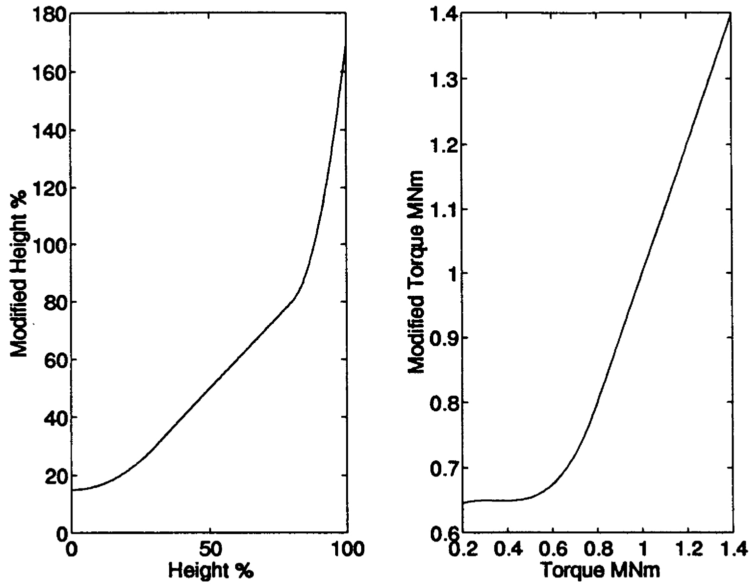

Figure 5.5: Nonlinear gain functions for the crushing process LQG controllers.

Coupled with the nonlinearity inserted for low chute heights is a converse problem with high end heights. Namely, at the top of the chute there is a need for maximum speed to avoid overflows. The control objective of torque regulation is countermanded by the impending breach of a constraint. Yet the signal gain in this case is too low to respond in this fashion, and even more so when the torque is simultaneously low (which is the usual situation). Therefore, to abide by this constraint at the top end it proves necessary to amplify the height gain above 80% and to reduce the torque gain below 0.8 MNm. This too is done by smooth nonlinear functions. To maintain controller stability, no weighting was applied to chute heights in range 30-80% nor to torques above 0.8 MNm. Figure 5.5 shows the nonlinear weightings applied to the chute height and torque inputs of the crushing process LQG controllers.

There is no feasible simple approach to accommodating such constraints in an LQG design. The above controller retro-fitting was regarded as an appropriate method for handling the constraints. It should be noted that the existing PID controllers operate with similar modifications selected from a design palette. For instance, they include saturating rate-limiters and logical gap detection to alleviate integral windup. Furthermore, the chute height/speed PI controllers are error-squared controllers which provide very large gain increases when significantly far from set-point. Note, that the error-squared controllers are implemented with a narrow deadband interval around the set-point. This prevents hunting which would otherwise occur since the error-squared controllers have zero gain at set-point. The advantage of control law with a non-linear addendum over an error-squared control law is that the non-linearity only gradually becomes active in the operating region where it is most needed, as opposed to the entire operating range.

Remark 5.5.1 Using a large input-output data sequence from the sugar cane crushing process, Bitmead and Wertz (1994) have shown that the nonlinear gain characteristic in the chute height / speed PI controller is emphasised during periods of "good" performance as evaluated by a GPC criterion. This result lends additional support for using a similar nonlinear gain characteristic in the proposed LQG controller.

Remark 5.5.2 Kothare *et al* (1994) present a framework for the study of LTIFD systems subject to input constraints. The design methodology includes anti-windup bumpless transfer compensation to minimise the adverse affects of any control input non-linearities. This approach, unlike the above *ad hoc* approach adopted for the sugar cane crushing mill, provides a general framework for the design of anti-windup systems, and is therefore not process specific.

Limit Cycling and Round-off Effects

During the development of the LQG controllers with non-linear weightings, limit cycling was experienced after a gap in the feed material emptied the chute. This occurred when the speed signal was restricted to lie only in the range 0–100%, but this saturation was introduced into the autoregression of the controller computation in an attempt to limit integral windup. This limit cycle did not appear until the chute height had dropped to close to zero and consisted of successive pairs of 0% and 100%. Once established, the cycle was measurement-independent. Relocation of the limiter in the control algorithm as per Åström and Wittenmark (1990) resolved this limit cycling problem.

The LQG controller algorithms for the crushing mills were implemented in FORTRAN. Single precision floating point arithmetic of FORTRAN was sufficient to avoid round-off problems in this application. Other implementations of these controllers have, however, led to such problems, especially with fixed-point computation.

5.6 Chapter Conclusion

For the sugar cane crushing process, the design of a 2ilo torque controller using LQG/LTR techniques requires the identification of 2ilo height and torque models from closed loop input-output data. Identification design variables, in particular excitation and data filtering, determine the outcome of the closed loop model fitting process and the resultant controller. Therefore, the selection of these design variables is of great importance. Chapter 6 details issues of identification design variable selection for the sugar cane crushing process. The treatment presented also investigates model assessment, data sequence selection, and model structure selection.

The crushing process application is not limited to the design of a one-off controller to achieve performance enhancement. The endeavour is to use the Zangscheme iterative identification and control design to enhance gradually closed loop performance through controller refinement. The successful application of the Zangscheme to the crushing process would not have been possible without fundamental research. This research addresses,

- the manner in which the original Zangscheme is implemented and possible variants which provide faster performance enhancement.
- a mechanism by which to apply the Zangscheme in a cautious manner.
- how the frequency weightings used in the Zangscheme controller design stage affect the resultant controller.

The results of this research are presented in Chapter 7.

Chapter 6

Closed Loop Identification of Sugar Cane Crushing Process Models

6.1 Chapter Motivation

Closed loop identification is often, due to production and safety reasons, the only method of identification available to industrial processes. In this sugar milling application, identified models are intended for feedback control design. During normal disturbance rejection operation, closed loop behaviour can heavily disguise the plant dynamics which are important in a realising control solution which attains high achieved performance. The problem occurs since in closed loop the plant input is correlated with the unknown disturbance. To emphasise the plant dynamics, closed loop identification should be undertaken using data collected with carefully chosen excitation signals superimposed on the plant inputs. The design variables available to the engineer to influence the plant model fitting are; the plant and disturbance model order and structure, and the experimental conditions including external excitation and data filtering.

In order to understand the closed loop model fitting process, associated design variable selection and model validation, the closed loop identification criterion, (3.6), is referred to extensively in this Chapter. This identification criterion is repeated below for the reader's benefit,

$$V_N(\theta) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \left\{ |P - \hat{P}(\theta)|^2 \Phi_r + |1 + C\hat{P}(\theta)|^2 \Phi_v \right\} \frac{|D|^2}{|1 + CP|^2 |\hat{H}(\theta)|^2} \, d\omega. \tag{6.1}$$

The ω dependence have been omitted deliberately.

For remainder of this thesis closed loop signals for scalar and multi-variable system will appear with the time index, k, at the subscript location.

6.2 The Need for Excitation during Closed Loop Identification

The closed loop identification criterion, (6.1), can now be interpreted for open loop and closed loop data. This section considers the need for excitation with the direct prediction error method of closed loop identification. Application of the indirect closed loop identification methods is clearly not possible without excitation.

6.2.1 Open Loop Identification

With open loop data the formula (6.1) is altered simply by setting the controller $C(z) \equiv 0$. In this case, the the open loop identification cost criterion (3.5) of Ljung (1987) is reproduced, where, in the absence of feedback, u_k now equals r_k, and is independent of v_k. Note, that a good working definition of "open loop" is that plant input, u_k, is independent of output disturbance, v_k.

Closed Loop Identification without Excitation

From Figure 2.1, page 14, with $r_k \equiv 0$, there are two algebraic relationships between the signals u_k and y_k, viz,

$$y_k = \hat{P}(z, \theta) u_k + v_k \tag{6.2}$$

$$y_k = -C^{-1}(z) u_k. \tag{6.3}$$

The first of these relationships, (6.2), is an inaccurate plant description, since there exists an unmeasurable disturbance process term and an ignorance of fundamental process modelling errors, while the second, (6.3), is precise and linear.

If it were feasible for $-C^{-1}(z)$ to be described within the model set, then the choice

$$\hat{P}(z,\theta) = -C^{-1}(z)$$

would yield a model which perfectly fits the data — no matter what the realisation of the disturbance v_k and independent of closed loop stability! This would seem to contradict the notion of fitting a model to the plant, however this is not entirely correct.

In the event that it is not possible to describe $-C^{-1}(z)$ exactly by a member of the model set $\theta \in D_{\mathcal{M}}$ one may appeal to (6.1) for insight into the selected model. The value of θ chosen will minimise the criterion,

$$V_N(\theta) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \left|\frac{1+\hat{P}(\theta)C}{1+PC}\right|^2 \frac{|D|^2}{|\hat{H}|^2}\, d\omega,$$

which still is accomplished by making $\hat{P} \approx -C^{-1}$. But this approximation is made most accurate at those frequencies where the denominator is small, that is where $P \approx -C^{-1}$. In this sense, closed loop identification without excitation does model the plant, but only where the closed loop sensitivity function is high.

One might be driven to conjecture that this fitting of a plant model which performs well precisely where the previous controller/model performed poorly was a good idea. However, the loss of information concerning the frequency bands where the performance was good or adequate usually outweighs any putative gains. As seen in Section 4.2, the Zangscheme iterative identification and control design builds on similar notions of controller modified model fitting, but with a relative model weight and with excitation. Identifying the inverse of the controller, while well known to most who have experimented with process data, is not a recommended practice, particularly when one (like ourselves) operates with PI feedback.

Remark 6.2.1 Initially it was thought that by selecting closed loop input-output data from periods of poor crushing process control, the plant behaviour would be emphasised over the controller action. This method, however, does not avoid the problems associated with fitting the plant model, not to the actual plant, but to the inverse of the controller.

6.2.2 Closed Loop Identification with Excitation

With feedback control plus an excitation signal, (6.1) indicates that identification of a model involves signal spectra, the controller, the disturbance model and the data filter. With *a priori* specified controllers and fixed noise models, this leaves the data filter and excitation spectra as the only free parameters. The selections of these design variables will be considered with respect to the requirements of robust control advanced in next section.

6.3 Design of Closed Loop Identification Experiments

6.3.1 Plant and Disturbance Characteristics

As foreshadowed in Chapter 5, plant input and disturbance changes are reflected in the deviation of mill operation from some nominal steady-state conditions. *A priori* approximations of the height and torque output signal behaviour gained from a physical understanding of mill operation and confirmed by open loop step response tests are summarised below.

1. Step variations in the plant input turbine speed s_k are reflected by negative ramp-like changes to the mill's chute height h_k output. Hence the crushing mill transfer function from speed to chute height, $P_{hs}(z)$, is known to contain an integrator. That is,

$$P_{hs}(z) = \frac{\bar{P}_{hs}(z)}{1 - z^{-1}}. \tag{6.4}$$

2. Step variations in the plant flap position f_k produce positive ramp-like changes to the mill chute height. Hence, the transfer function from flap position to chute height, $P_{hf}(z)$, also contains an integrator,

$$P_{hf}(z) = \frac{\bar{P}_{hf}(z)}{1 - z^{-1}}. \tag{6.5}$$

3. Step variations in the plant input turbine speed are reflected by negative step-like changes to the mill's turbine torque output. Hence, the crushing mill transfer function from speed to torque, $P_{ts}(z)$, does not contain an integrator.

4. Step changes to the flap position f_k produce step changes in the mill torque. Hence, the transfer function from flap position to torque, $P_{tf}(z)$, does not contain an inte-

grator.

5. Cane variety disturbances, v_k^h, to the mill chute height appear as ramps. That is, the deviations from steady operating conditions under constant speed are manifested as ramp-like changes in the chute height due to their effect on the feeding properties of the mill.

6. Cane variety disturbances, v_k^t, to the mill torque appear as steps. That is, the deviations from the steady operating conditions under constant speed and flap position are observed as step-like changes of the mill torque..

The identification of a 2i2o crushing process model consists of the combining the 2i1o height and torque models identified using prediction errors routines available in the MATLAB System Identification Toolbox (Ljung, 1991). Models from the Prediction Error Method program, *pem*, have the general form

$$A(z)y_k = z^{-l_1}\frac{B_1(z)}{F_1(z)}u_k^1 + \ldots + z^{-l_n}\frac{B_n(z)}{F_n(z)}u_k^n + \frac{C(z)}{E(z)}e_k,$$

where $l_1, \ldots, l_n$, are the delays associated with the corresponding plant inputs. The identification experiment involves the injection of external excitation signals, r_k^s and r_k^f (refer Figure 6.1), applied through the plant inputs of turbine speed, s_k, and flap position, f_k. The excitation signal design and to a lesser extent the data filter selection involve a thought experiment which uses the above *a priori* crushing process characteristics.

6.3.2 Excitation Signal Design

Excitation to overcome feedback

Analysis of (6.1) indicates that the purposes for choosing the excitation signal, r_k, are that the identification of the plant $P(z)$ be feasible across the bandwidth of interest, and that in this area of interest,

$$\left|P(e^{j\omega}) - \hat{P}(e^{j\omega}, \theta)\right|^2 \Phi_r(\omega) \gg \left|1 + \hat{P}(e^{j\omega}, \theta)C(e^{j\omega})\right|^2 \Phi_v(\omega). \tag{6.6}$$

That is to say, the external excitation signal spectrum, Φ_r, is an instrument to enforce the predominance of the $P \approx \hat{P}$ objective over the $P \approx -C^{-1}$ tendency.

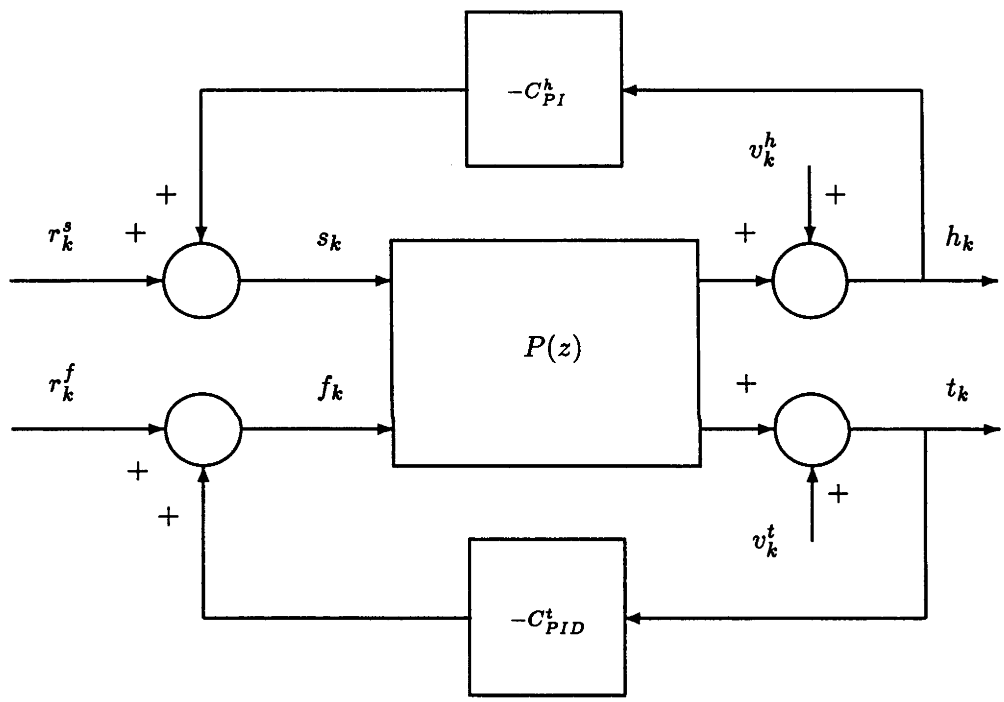

Figure 6.1: Identification of Plant Models in Closed Loop with Excitation

Excitation Signal Selection

Lemmata 4.1 and 4.2 given in Section 4.2 detail the choice of excitation design variables for the direct closed loop identification of plant models which are robust, either in a performance or a stability sense, with respect to the current controller. The excitation signal selections described by these two lemmata are :-

1. for robust performance select the excitation signal which is concentrated in the frequency bands of the plant disturbance.

2. for robust stability select the excitation signal to be broadband over the frequency range of interest, and such that it has significant energy in order that (6.6) holds over the band of interest in the case of direct closed loop identification.

Both excitation signal choices listed above are linked also to the selection of the $D(z)$ identification data filter in that both the excitation signal spectrum and the data filter frequency response determine the ultimate shaping of the frequency weighted model fit effected by minimising (6.1). (D shall again, shortly, be reconsidered.)

Remark 6.3.1 The disturbance processes, v_k^h and v_k^t, are modelled as being ramp-like and step-like. These disturbances have very strong weighting in the low frequency region. To counteract this, the excitation signals, r_k^s and r_k^f, must also be chosen to emphasise these frequencies and, at least, to overcome the disturbances here.

Remark 6.3.2 The excitation signals need to be broadband signals with an emphasis in the middle to low frequencies. This reflects the potential usage of the model to design a controller capable of pushing the closed loop bandwidth to roughly 0.2 Hz (1.26 rad/sec) at a sampling rate of 1 Hz.

Remark 6.3.3 Balanced against the desire to *blast* the mill with very large external excitation and so identify a very good model, are the constraints of the permissible or possible ranges for the process variables; torque, chute height, chute flap position and turbine speed. This is to be taken into account together with the constraints imposed by the conduct of the identification experiment during productive operation of the mill.

Remark 6.3.4 The sugar cane crushing process can be subjected to excitation signals much larger than for many other manufacturing processes since the product quality remains relatively unaffected. Generally, by performing identification experiments one at a time, the injection of excitation has a minimal impact on the overall crushing process performance. In addition, the crushing process is a relatively fast process industry plant which requires sampling frequency of 1 Hz to capture the important process dynamics. Therefore, an identification experiment lasting one hour normally provides sufficient data (3600 samples) from which suitable data batches can be selected, not only for model fitting, but just as importantly for model validation.

6.3.3 Data Filter Design

The data filter is applied to all the data prior to the use of a standard identification package. Data filtering has two principal purposes,

- to remove specific out-of-band disturbance signals which are known *a priori* and which do not contribute any useful information for control purposes.
- to precondition the data to effect the frequency weighting in (6.1).

As shown in Section 4.2, the preconditioning by data filtering together with the plant excitation can be selected in a manner so as to influence robustness.

Differencer Justification

The justification for incorporating a differencer in the data filter includes :-

- the removal of known redundancies in the disturbance model, e.g. in the case of height model the height disturbance, v_k^h, is known to be ramp-like and so one degree of freedom is being wasted in modelling this extra model in E. If the data h_k, s_k and f_k are replaced by differenced data, $\tilde{h}_k$, $\tilde{s}_k$ and $\tilde{f}_k$, that is

$$A(z)h_k = z^{-l_1}\frac{B_1(z)}{F_1(z)}s_k + z^{-l_2}\frac{B_2(z)}{F_2(z)}f_k + \frac{C(z)}{(1-z^{-1})E'(z)}e_k$$

  is replaced by

$$A(z)\tilde{h}_k = z^{-l_1}\frac{B_1(z)}{F_1(z)}\tilde{s}_k + z^{-l_2}\frac{B_2(z)}{F_2(z)}\tilde{f}_k + \frac{C(z)}{E'(z)}e_k,$$

  then the free parameters in E' may be used to model other plant disturbances, not *a priori* known.

- the objective of modelling $P(z)$ by $\hat{P}(z,\theta)$ is not matching open loop models but rather closed loop models, refer Zang *et al*, (1994, 1991), Schrama (1992a), Gevers and Ljung, (1986). That is, the identification criterion should have a performance degradation form where the objective is to keep the achieved and designed closed loop sensitivity mismatch small. The sensitivity mismatch can be defined as,

$$\begin{aligned}\hat{S}(e^{j\omega}) - S(e^{j\omega},\theta) &\triangleq \frac{1}{1+C(e^{j\omega})\hat{P}(e^{j\omega},\theta)} - \frac{1}{1+C(e^{j\omega})P(e^{j\omega})} \\ &= \frac{C(e^{j\omega})\left[P(e^{j\omega}) - \hat{P}(e^{j\omega},\theta)\right]}{\left[1+C(e^{j\omega})\hat{P}(e^{j\omega},\theta)\right]\left[1+C(e^{j\omega})\hat{P}(e^{j\omega},\theta)\right]}. \end{aligned} \tag{6.7}$$

  Assuming that the excitations are chosen to cause the satisfaction of (6.6) and, further, this is done as above by injecting signals, r_k, with spectra close to $|\hat{H}(e^{j\omega},\theta)|^2$, then the identification criterion (6.1) acquires the form,

$$V_N(\theta) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \frac{|P-\hat{P}|^2|\hat{H}|^2}{|1+PC|^2} \times \frac{|D|^2}{|\hat{H}|^2}\, d\omega.$$

  Comparing this expression with (6.7) above, modelling to reduce sensitivity error can be performed by selecting

$$D(e^{j\omega}) = \frac{C(e^{j\omega})}{1+P^{\dagger}(e^{j\omega})C(e^{j\omega})}.$$

  Here $P^{\dagger}$ indicates an estimate of the likely plant model based on *a priori* data. For the sugar cane crushing process under PID or LQG control, *a priori* information indicates that C should contain an integrator for both the chute height and torque loop, while $P_h^{\dagger}$ also contains an integrator. Based on these considerations and the above recommendation for the selection of D towards minimising performance degradation, it is apparent that D ought to include a differencing function.

The effect of including a differencer is to force the identifier to fit the plant model in the medium to high frequency range. Since a closed loop bandwidth of around 0.2 Hz is desired, the suitability of a model fit weighted toward the high frequency end of the spectrum evanesces. Therefore, a broad low pass filter is also included in the data filter to de-emphasise the model fit at high frequencies, whilst at the same time weighting the importance of the model fit at low to moderate frequencies. In addition to the low pass filter, very low pass excitation with integral action in the plant and controller may extend the bandwidth of model fit to the low frequencies.

Data Filtering to remove dc offsets and sinusoids

One feature which from (6.1) is very critical in the selection of the data filter, D, is the removal of dominant sinusoidals and dc offsets present in the disturbance, v_k, and not overwhelmed by sinusoids and dc offsets in the excitation, r_k. In signal terms, their effect is that they are present in plant output, y_k, due to v_k and then, because of feedback, appear in the plant input, u_k. The low-pass nature of the controller, C, will diminish the magnitude of sinusoids appearing in u_k, whilst the dc offsets will be multiplied by the steady-state controller gain. Any modelling which fails to remove these signals will attempt to fit a high gain plant at the sinusoidal frequency and possibly an incorrect plant model steady-state gain. Sinusoids can be readily removed by including a notch filter in the data filter. The dc offsets are removed from both input and output signals by detrending the data prior to data filtering.

Remark 6.3.5 With the sugar mill problem, the elevator tines shown in Figure 5.1 deliver the bagasse in discrete wads at a fixed rate governed by the elevator motor speed. This causes a periodic disturbance to the chute height signal with period of 3.4 sec. Before passing data to the identifier, it was passed through a *tinesucker* filter tuned to notch out this periodic signal. On other mills, actuator bouncing has also been removed using D with another notch located at the frequency at which the actuator bounces. By extracting these signals, one avoids the need to introduce higher order disturbance models.

Remark 6.3.6 The effect of detrending the data is to position a narrow notch at dc in the frequency spectrum of the data. Using least squares minimisation identification methods the dc notch is smoothed out in the identified plant model.

6.3.4 Data Sequence Selection

The two separate 1 Hz sampled data sequences from a single one hour duration closed loop identification experiment were chosen for model identification and model assessment. The data sequences were typically 1000 data points long (16.67 minutes of operation). The criterion for selecting a data sequence includes inspecting the data to ensure :-

- persistent excitation of the process variables. That is, the process variables are not to be, constant, either, due to gaps in the supply of the feed material or production stoppages. Whilst the process variables are constant only steady state information about the process dynamics can be discerned.

- that the process variables are not close to or equal to their constraint values. Process operation close to constraint values will introduce non-linearities into the data which could adversely affect the performance of linear System Identification methods. Recall from Section 5.5.2 that the implemented controllers, LQG and PID, include a non-linear addenda which becomes effective when the process outputs are close to their constraint values.

- the effect of cane variety disturbance on the process variables appears stationary and does not dominant over the injected input excitation for the length of the data sequence. Linear System Identification methods are intended for use with either stationary or quasi-stationary data, and not with data which is non-stationary. The consequences of using non-stationary data is that the change in plant disturbance statistics could incorrectly be attributed to the plant transfer function dynamics.

6.3.5 Model Structure Selection

The initial height and torque models were identified from closed loop PID data using an ARMAX model structure with unity delay. Subsequent model identifications during the iterative identification and controller design procedure used a Box-Jenkins structure with larger delay. Box-Jenkins models are characterised by independently parametrized plant and disturbance models. In hindsight, the Box-Jenkins model structure with delay is better suited to the disturbance driven sugar cane crushing process than an ARMAX model structure since the disturbance process is primarily determined by the physical properties of the sugar cane rather than the mechanical setup of the individual crushing units.

Second order plant dynamics (and in the case of identified Box-Jenkins models – long delays) were identified, with sufficient disturbance model order to ensure that modelling errors due to quantization, offsets, and non-stationarity, would be largely accommodated in the disturbance model rather than in the plant model. The identified plant and disturbance models were checked against the *a priori* process knowledge outlined in Section 6.3.1. Higher plant model order, despite minimising the loss function (3.4), failed to deliver plant models compliant with the *a priori* model assessment check.

6.3.6 Model Assessment

The above *a priori* process behaviour can be used to formulate a simple model assessment check. The checks on the identified models include verifying that:-

- the shape of the frequency response plot is low pass without any resonance peaks.
- the steady-state gains are in an acceptable range.
- the steady-state phases are correct.
- the open loop step response test displays a slow rise time and an overdamped response. In the case of the identified transfer function, $\hat{P}_{hf}$, an underdamped response with small overshoot and a very low natural oscillation frequency are consistent with the effect of bagasse compaction in the feed chute.
- the frequency response of the identified disturbance model is low-pass with considerable energy.

Traditional model validation checks performed with fresh data (Ljung, 1991) included,

- a test of the residuals associated with the data and a given model. The residuals should be ideally white and uncorrelated with the model input and output.
- a time domain comparison of the predicted model output at several step-ahead versus the true plant output.

With complex industrial processes such as the sugar cane crushing process, by themselves the traditional model validation checks would have resulted in model acceptance despite model behaviour contrary to *a priori* process information. Therefore, the acceptance of a plant model for controller design is conditional upon the success of a model assessment check using *a priori* process behaviour. The traditional model validation checks provides a secondary, less stringent, test.

6.4 Experimental Results

6.4.1 The Need For Excitation

The data used to obtain the results presented in this Section came from an identification experiment performed on the crushing process. Fresh crushing process data was used for the model validation checks. The term *process data* refers the input-output data which represents both signals measured by field sensors and control signals sent to manipulate process actuators. In other words, **no** computer simulation generated input-output data was used for, either, the model fitting or model validation of the identified plant models described in this chapter.

Two closed loop experiments were performed on the sugar mill operating under PID feedback control as in Figure 6.1, i.e. PI feedback from chute height to turbine speed and PID control from turbine torque to chute flap. Using the direct prediction error method of closed loop identification, 2-input 1-output models were fitted with ARMAX models with second order plant dynamics and unity delay plus a second order disturbance process. In the first experiment, no external excitation was added into the closed loop. The second experiment was performed with :-

- a speed excitation signal, r_k^s, chosen as doubly integrated white noise with a standard deviation of $\pm 10\%$ of full scale deflection,
- a flap position excitation signal, r_k^f, chosen as doubly integrated white noise with a standard deviation of $\pm 20\%$ of full scale deflection,

chosen based on the guidelines in Section 6.3.2. The data filter chosen as per Section 6.3.3 included :-

- a *tinesucker* notch filter with narrow and deep notches at 0.29 Hz and its second harmonic.
- a third order low-pass butterworth filter with a cutoff at 0.2 Hz.
- a differencer.

Remark 6.4.1 The selections of excitation signals are somewhat heuristically based on the validity of the single-input theory of Section 3 applying directly to the multi-input case. The multi-variable case is described in Appendix A.

Remark 6.4.2 The multi-variable nature of the plant prevents the independent specification of spectra of r_k^s and r_k^f in the separate identification of chute height and torque models. For this latter model one might reasonably expect that the choice of doubly integrated white noise would overly exceed the step-like disturbance process. However, the feedback connection of the ramp-like v_k^h into the torque loop via the PI speed/height loop, also needs to be taken into account.

Remark 6.4.3 The above selection of excitation and data filtering, recalling that the disturbance energy is concentrated in the low frequency band, is aligned with a controller design tending toward robust performance rather than robust stability.

Figure 6.2 shows the identified transfer function magnitudes from speed to chute height and from chute flap to chute height from the first experiment. The transfer functions exhibit the characteristic effect presaged in Section 4 of modelling the negative inverse of the controller. Here the controller inverse is not realizable because of causality constraints. However, the inverse PI approximation is clear and the steady state phase of the speed to height transfer function is opposite that of the controller. Figure 6.2 also illustrates the equivalent plots when the excitation is added. Now the identified plant model conforms to physical expectations in both magnitude and phase.

Figure 6.3 demonstrates a similar effect for the identified torque models in the respective cases. The image here is changed to reflect the modelling of the derivative action at high frequencies. These practical experiments reinforce the theory advanced in Chapter 3 and the excitation signal design of Section 6.3.2.

One might be drawn to ask why the model fit to the controller inverse was not exact in these examples. One reason has been given already; that the non-causality of this inverse requires that it be approximated by the model. Other features influencing the model fit also include the effects of data quantization (4 bits in the chute height for example) and nonlinear implementation in the PI and PID controller due to rate limiters and the like. These nuances notwithstanding, the experiments in closed loop design amply demonstrate the principles.

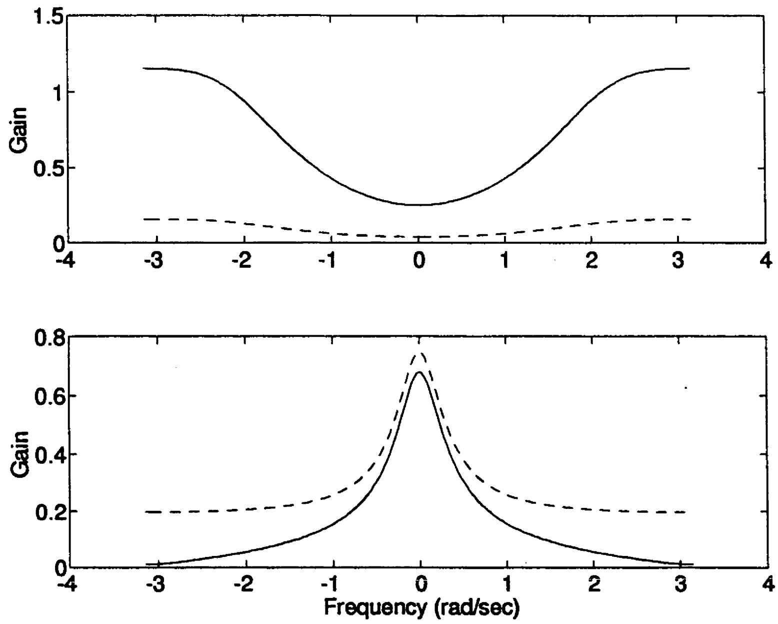

Figure 6.2: Frequency response of A2 mill height models identified in closed loop from non-excited (top) and excited (bottom) data. Speed to height transfer function model (solid line), flap to height transfer function model (dashed line).

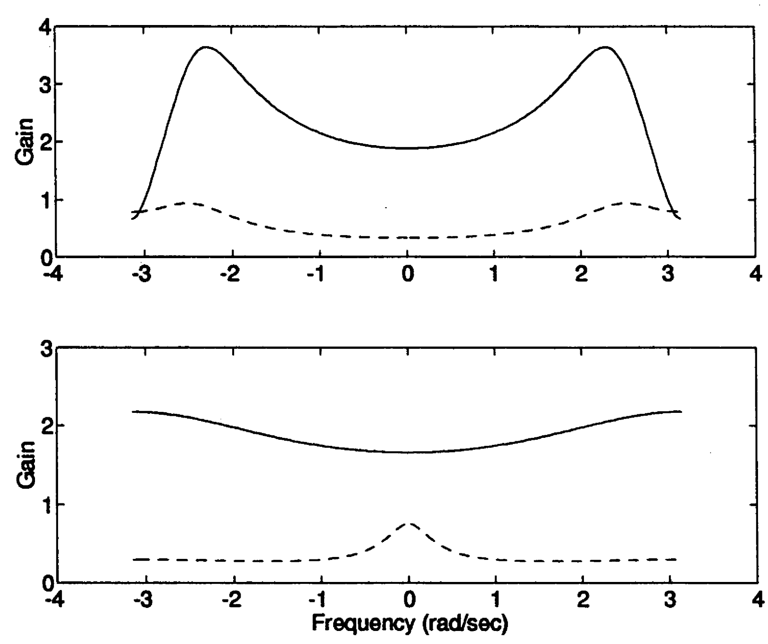

Figure 6.3: Frequency response of A2 mill torque models identified in closed loop from non-excited (top) and excited (bottom) data. Speed to torque transfer function model (solid line), flap to torque transfer function model (dashed line).

6.4.2 Direct versus Two-stage Indirect Method

Model Fitting

The application of an iterative identification and controller design to the sugar cane crushing process presented an opportunity to compare the direct prediction error and the two-stage indirect methods of closed loop identification for restricted complexity models. The dual-Youla parametrization identification was not considered as the updated R-parametrized plant models are generally of such a high order that model reduction is required. In many respects, the normalised coprime factor identification is conceptually similar to the easier to comprehend two-stage indirect identification method. For this reason, the two-stage indirect method was preferred to the normalised coprime factor identification.

The same excitation signal spectra described in Section 6.3.2 were applied with larger amplitude magnitude during the closed loop identification experiment with the current LQG controller of the revised Zangscheme operating on A2 mill. A detrended data sequence from this experiment was filtered using a data filter consisting of a broad low-pass filter and *tinesucker* notch filter, prior to a minimisation search for plant models using the two-stage indirect and direct prediction error method of closed loop identification. Although use of a differencer in the data filter can be theoretically justified, recall Section 6.3.3, the reality is that the frequency weighting effected by the differencer is too severe. After the first iteration, a differencer was not included in the data filter as it was found to de-emphasise the low frequency band excessively, which is the frequency range of interest for plant models which are suitable for control. The differencer was replaced by a zero-order detrender, which proved adequate to remove quantization effects.

Figures 6.4 and 6.5 illustrate the comparative step and frequency response plots of the identified height models, respectively. Similarly with Figures 6.6 and 6.7 for the torque model. Figure 6.8 compares the step responses of LQG controllers designed on the basis of height and torque models identified by the two methods. Table 6.1 displays the delays associated with the identified plant models.

Remark 6.4.4 All identified models are of Box-Jenkins structure with long delay plus second order dynamics and third order disturbance processes.

Remark 6.4.5 The first open loop identification in the two-stage indirect method iden-

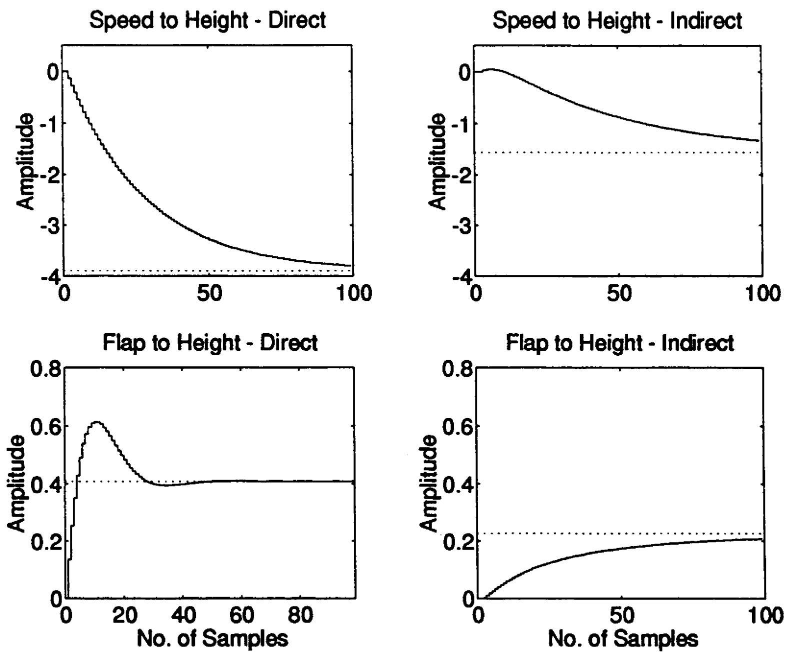

Figure 6.4: Step responses of the height model identified using the direct (left) and the two-stage indirect(right) methods of closed loop identification.

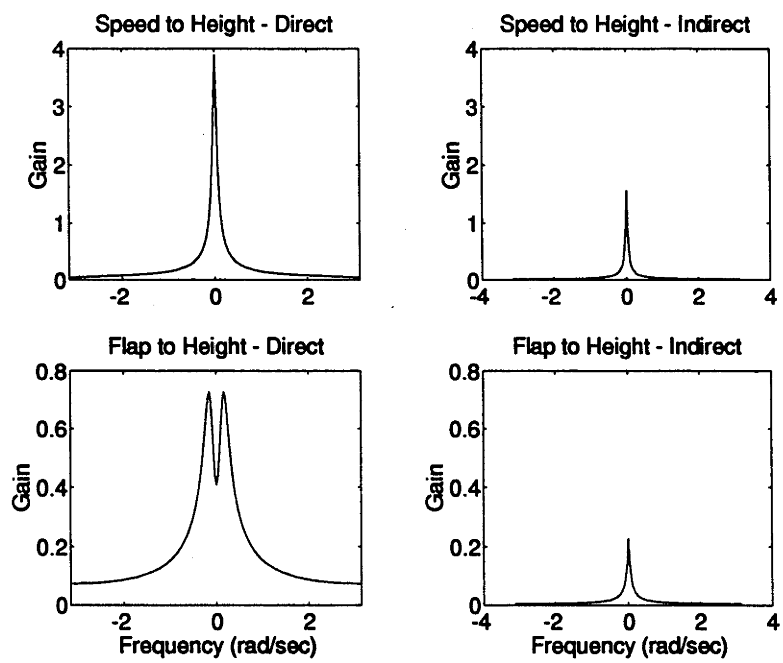

Figure 6.5: Frequency responses of the height model identified using the direct (left) and two-stage indirect(right) methods of closed loop identification.

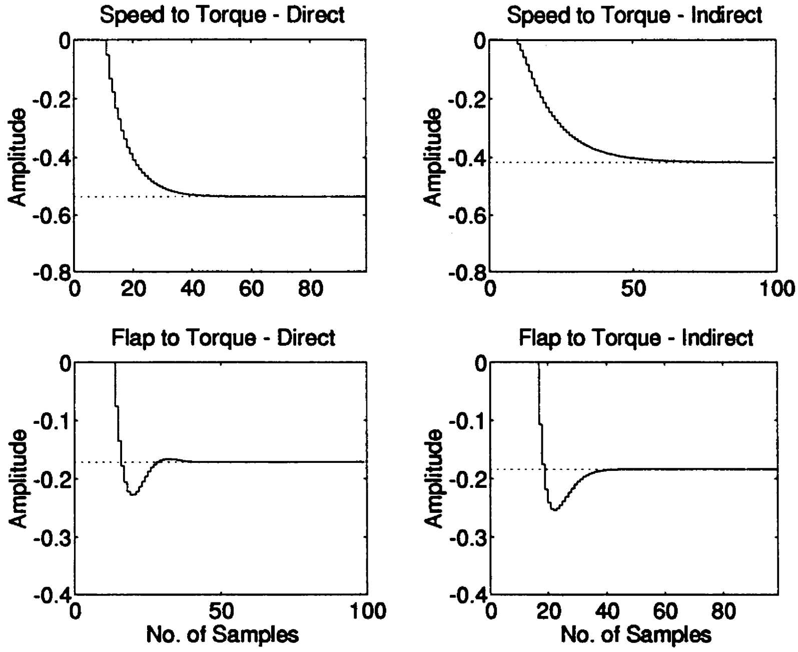

Figure 6.6: Step responses of the torque model identified using the direct (left) and two-stage indirect(right) methods of closed loop identification.

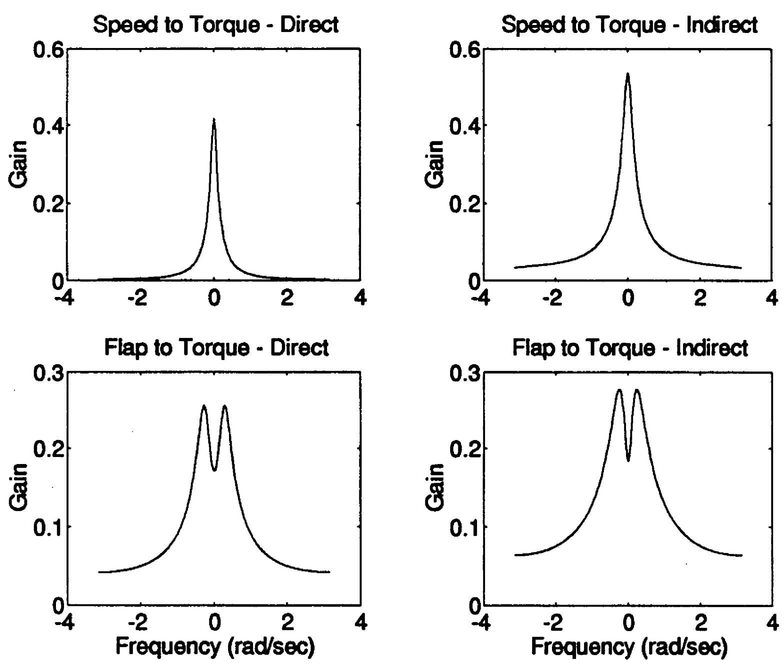

Figure 6.7: Frequency responses of the torque model identified using the direct (left) and the two-stage indirect(right) methods of closed loop identification.

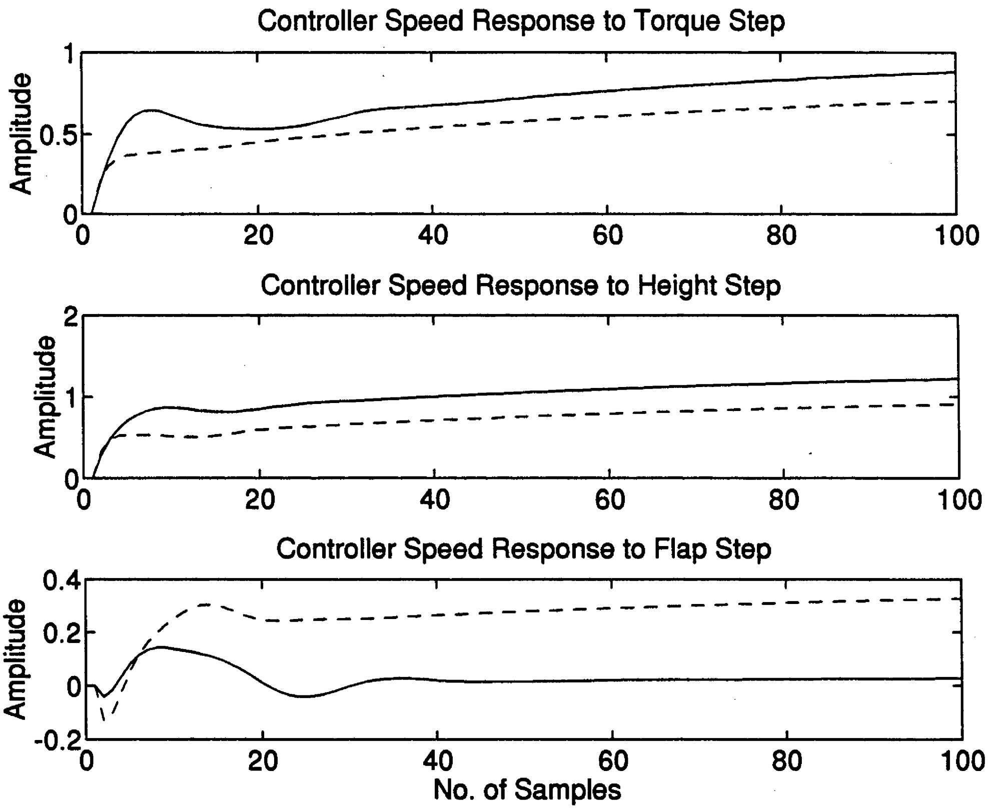

Figure 6.8: LQG torque controllers' speed response to steps in the input and disturbance variables. Controller, C_2 (dashed line), designed using models identified via direct prediction error method. Controller, C_2 (solid line), designed using models identified using the two-stage indirect closed loop identification method.

tified SISO Box-Jenkins models made up of an eighth order sensitivity function model with zero delay and a tenth order noise model. Using MATLAB software provided by the Measurement and Control Group, Delft University of Technology, The Netherlands, it has also been verified that a third order series expansion of Laguerre orthonormal basis can provide sufficiently accurate of the sensitivity functions associated with the sugar cane crushing process.

Remark 6.4.6 Assuming an ARX model structure the MATLAB System Identification Toolbox command *arxstruc* (Ljung, 1991) can be used to determine the optimal model order according to some criterion, e.g. Akaike's information theoretic criterion (AIC), Rissanen's minimum description length (MDL). Although second order Box-Jenkins models are utilised for the sugar cane crushing models, the *arxstruc* command can still be used, with a fixed model order, to obtain a set of candidate values for the input delay to be used during the fitting of the Box-Jenkins models. The set of candidate delay values was chosen around the "knee-point" of a loss function versus delay magnitude plot. During the model fitting process, these candidate delay lengths and also various disturbance model orders were used in a trial and error fashion in conjunction with the model assessment checks before arriving at the final Box-Jenkins plant model.

Remark 6.4.7 The choice of excitation results in an identification experiment designed to deliver data that will result in the identification of plant models for robust performance controller design. Some robust performance is compromised for robust stability through the choice of data filtering (recall Section 4.2.2).

Remark 6.4.8 The *pem* command from MATLAB System Identification ToolBox (Ljung, 1991) was used to identify all plant models described in this paper. The *pem* program defaults to a maximum of 10 iterations of a Gauss-Newton minimisation procedure in a search for the parameter vector with the minimum prediction error (3.8). During the application of the *pem* algorithm with both methods of closed loop identification, the identified plant models from the early iterations were found to comply with the model assessment checks outlined in Section 6.3.6. Further iterations produced a lower loss function (3.4), at the expense of process behaviour consistent with *a priori* knowledge. It could be argued that since successive *pem* iterations gave models which did not comply with *a priori* knowledge, then the obtained models are not good predictors of the unknown system. Therefore,

Outputs	Direct Method		Indirect Method	
	Inputs		Inputs	
	Speed	Flap	Speed	Flap
Height	2	1	3	3
Torque	11	14	9	17

Table 6.1: Delay Magnitudes for Height and Torque Models. Direct Method vs. Two-stage Indirect Method.

models chosen from early *pem* iterations which pass the model assessment tests, including validation, can be considered to be good predictors of the unknown system. Despite some academic opinion, such models could be used with confidence to derive a controller.

Remark 6.4.9 As indicated in Chapter 2, the true system is being idealised as a LTI system. This idealisation provides a mechanism for realising and implementing sub-optimal model-based controllers for the difficult to control sugar cane crushing process. Of course, an optimal controller is preferable, however for this process a truly optimal controller cannot be designed, let alone be implemented. Better an approximate solution than none at all.

Remark 6.4.10 Figures 6.4 and 6.5 show a considerable difference between the height models identified by the two methods. Direct prediction error method produces height models with too much steady state gain in the speed channel. The two-stage indirect method identifies non-minimum phase behaviour in the speed channel for the height model. This slight non-minimum phase action is consistent with back pressures in the crushing mill preventing the passage of material after a speed increase.

Remark 6.4.11 Figures 6.6 and 6.7 display similar torque models resulting from both identification methods.

Suitability of Identified Model for Control

The height and torque models identified using both the direct and two-stage indirect closed loop identification methods were used in the design of two separate 2i1o LQG torque controllers. Recall from Section 5.3.1 that for given control penalty, the torque controllers are designed to minimise a weighted torque and height objective. In this 2i1o torque controller, the flap position output signal from the override PID torque controller was treated as a measurable disturbance. Figure 6.8 shows the step response of two resulting 2i1o LQG torque controllers,

1. C_2^{dir} designed using the height and torque models identified using the direct prediction error method of closed loop identification,

2. C_2 designed using height and torque models identified by the two-stage indirect closed loop identification method.

Controller, C_2, significantly improved the control performance of A2 milling unit by almost halving the standard deviation of torque excursion from set-point associated the previous LQG and PID controllers. The controller, C_2^{dir}, performed in manner similar to the previous LQG and PID controllers. Contributing factors to superior performance of C_2 over C_2^{dir} are :-

- the larger response of the speed to steps in the torque and chute height.

- the almost complete rejection of the steady state flap position after some initial control action.

The first factor can be related to characteristics of the identified models. The large steady state gain in the speed channel of the height model identified using the direct closed identification method meant that the controller, C_2^{dir}, did not have sufficient gain to allow the control action to bring the process variables back to set-point.

It is difficult to gauge from the frequency and step response plots of the flap to height model and the flap to torque model in Figures 6.4 and 6.5 and Figures 6.6 and 6.7, respectively, as to exactly why the controller, C_2, did not respond to the steady state flap position. It should be noted that with the both the flap to height and torque to flap models possess a zero located near the steady state frequency (dc). The response of controller, C_2, to step variations in the measurable disturbance flap position signal is in accordance with *a priori* knowledge, which suggests that variations in the flap position directly affect the chute height, and that the steady state flap position has very little effect on chute height due to compaction in the feed chute. Hence, zero steady state gain from flap position to speed in the LQG torque is highly desirable. Note with controller, C_2^{dir}, the steady state flap position introduces an offset to the final speed control value.

Appraisal

In this application, the two-stage indirect method of closed loop identification resulted in models that produced superior controllers to those designed using models obtained through direct prediction error closed loop identification. It should be noted that both controller designs used the same inexact disturbance models formulated from *a priori* information. Due to the idealisations made about this industrial application, it is difficult to pinpoint the exact contributing factors for the superiority of one torque controller over the other. The main difference between the two closed loop identification methods used to derive the height and torque models, for the controller design, is that with the two-stage indirect method the unknown disturbance spectrum does not contribute to the minimisation of prediction errors. This is not necessarily the case with direct prediction error identification, and could have resulted in the identification of models which possessed a bias that was detrimental to achieving high closed loop performance on the true system. Recall from Remarks 3.3.5 and 4.2.9 that a biased plant may not necessarily have adverse consequences for closed loop control.

Obviously the issue of resolving which approach to closed loop identification, direct or indirect, is capable of delivering models that are superior for purposes of designing disturbance rejection controllers for processes characterised approximately by linear time-invariant systems, remains largely unanswered[1]. For the process control practitioner this is an important question.

6.5 Chapter Conclusion

For the sugar cane crushing process, closed loop identification performed with appropriately chosen design variables can provide adequate models for control design. It has been shown that thought experiments which use *a priori* process knowledge can be used to motivate the selection of identification design variables. Closed loop identification is merely a mathematical tool for obtaining plant models. As such, the designer needs to focus the use of this mathematical tool towards delivering plant models which pass model acceptance tests. Most mathematical tools are designed to work best when no system idealisation is required. However, for most industrial applications where the degree of idealisation may

[1] Despite the assertions of rumour, hearsay, and innuendo.

be significant, in general, closed loop identification techniques need to be cajoled heavily in order to produce a model which the designer is confident to use in a subsequent controller design. This chapter has presented some practical insights into how the user may pamper closed loop identification techniques to achieve this objective. For the process control practitioner the importance of providing insights into how such design variables might be selected should not be underestimated, and as such constitutes a valid research goal.

Chapter 7

The Revised Zangscheme

7.1 Chapter Motivation

The Zangscheme is a signal-based iterative identification and control design method. This iterative scheme features model adjustment through frequency weighted least squares identification followed by controller enhancement via frequency weighted LQG design. Different frequency weightings are used during the model adjustment and controller enhancement phases. The aim of each Zangscheme iteration is to ameliorate the achieved closed loop performance. By altering the manner in which the Zangscheme is performed, a number of variants to the original Zangscheme are possible.

The first variant to the original Zangscheme partially decouples the model adjustment and controller enhancement phases. This is achieved by altering the sequence of steps in the original Zangscheme algorithm. This means that the current iteration of the Zangscheme is no longer dependent directly upon the model adjustment phase of the previous iteration. The controller design criterion induced by this variant reduces the extent of possible controller parameter misadjustment compared with the original Zangscheme. This variant is designated as the **decoupled variant**.

The second variant permits the direct adjustment of controller parameters without the need for a model adjustment. The advantage of this scheme is that it obviates the need for an identification experiment and the selection of identification design variables such as excitation signals and data filtering. This variant is known as the **direct variant**.

The Zangscheme controller results from the optimisation of an LQ performance criterion. This involves solving an algebraic Riccati equation. As such, the resultant adjustment to the controller parameters may not necessarily be cautious. However, by scaling the effect of the frequency weightings, the modification to the controller parameters will be as conservative as the user desires. Naturally, this is provided that the previous adjustment to the model parameters is not too great.

Variants to the original Zangscheme with scalable frequency weightings are detailed in this chapter. These alterations to the original Zangscheme are used to motivate a revised Zangscheme algorithm for the sugar mill application.

The cornerstone of the Zangscheme iterative design is the frequency weighting derived from operational data. These frequency weightings provide a transformation which connects the achieved and designed closed loop systems. By examining an innovations-like signal called the **predicted difference** in the achieved closed loop, it becomes apparent that including frequency weightings in the controller design has the effect of whitening the predicted signal of the achieved closed loop systems. In an optimal LQG controller, it is well known that the Kalman predictor innovation signal is white. Therefore, examining the whiteness of an innovations-like signal given that the true innovations signal may not be accessible, is one way of assessing the merit of particular control design procedure. Without a frequency weighted LQG controller design the predicted difference signals associated with the achieved closed loop systems are not whitened. Details of this result are presented in the latter part of this Chapter, where some of its implications are also discussed.

7.2 The Original Zangscheme

The formulation of the original Zangscheme for the disturbance rejection control of SISO systems has already been motivated in Section 4.2. Pertinent aspects of this design methodology are repeated for the reader's benefit. The original Zangscheme consists of a model adjustment step followed by a controller enhancement. The model adjustment step is performed using direct prediction error identification to minimise the error between corresponding closed loop signals in the achieved and designed systems (recall identification criterion, (4.7)),

$$J_{H_2}^{pd} = \frac{1}{N}\sum_{t=1}^{N}(y_k - y_k^c)^2 + \lambda(u_k - u_k^c)^2. \tag{7.1}$$

With the controller enhancement step, an updated controller, C_{i+1}, results from the minimisation of the following frequency weighted LQG criterion (recall criterion (4.4)),

$$C_{i+1} = \arg\min_{C \in \mathcal{C}} \frac{1}{N} \left[\sum_{k=1}^{N} \hat{F}^2(P, \hat{P}_i, C_i)[(y_k^c(\hat{P}_{i+1}, C))^2 + \lambda[u_k^c(\hat{P}_{i+1}, C)]^2 \right], \tag{7.2}$$

where the frequency weighting, F, used in this criterion is defined by,

$$\left.\begin{array}{c} F = F_1 = F_2, \\ F_1 = \{\frac{\Phi_y}{\Phi_{y^c}}\}^{1/2} \;\; ; \;\; F_2 = \{\frac{\Phi_u}{\Phi_{u^c}}\}^{1/2}. \end{array}\right\} \tag{7.3}$$

The steps within the $(i+1)-$th iteration of the original Zangscheme can be summarised as follows :-

1. Perform a closed loop experiment with a fixed controller, C_i, acting upon the true plant, P, with an external excitation signal, r_k, added to the plant input, as in Figure 2.1, page 14, to generate a data set, $\{y_k, u_k\}$, of length N.

2. Perform a closed loop simulation with the same fixed controller, C_i, acting upon the plant model, $\hat{P}_i(\theta)$, as in Figure 2.2, page 25, to generate a data set, $\{y_k^c, u_k^c\}$, of length N.

3. Compute the data filter, D_{i+1}, according to

$$D_{i+1} = \frac{\hat{H}_i G_i}{1 + C_i \hat{P}_i(\theta)}, \tag{7.4}$$

where

$$G_i G_i^* = 1 + \lambda C_i C_i^*, \tag{7.5}$$

as per Lemma 4.1.

4. With the data set obtained by experiment and simulation and using direct prediction error closed identification :-

   - identify $\hat{P}_{i+1}(\theta)$ using D_{i+1}.
   - identify autoregressive (AR) models of y_k, u_k, y_k^c, u_k^c to approximate, respectively, $\Phi_y^{\frac{1}{2}}, \Phi_u^{\frac{1}{2}}, \Phi_{y^c}^{\frac{1}{2}}, \Phi_{u^c}^{\frac{1}{2}}$ (recall Section 4.2).

5. Calculate the frequency weighting estimates, $\hat{F}_1$ and $\hat{F}_2$, according to (7.3).

6. Design a frequency weighted controller, C_{i+1}, based on the plant model, $\hat{P}_{i+1}(\theta)$, and the identified signal spectra, by minimising (7.2).

The model adjustment and controller enhancement steps of the current and previous iteration of the original Zangscheme are considered to be coupled since a single iteration produces $\hat{P}_{i+1}, C_{i+1}$ from weightings which either wholely or partly depend upon quantities, $\hat{P}_i, C_i$, from the previous iteration.

Remark 7.2.1 The identification criterion used during the model adjustment depends upon the user requirements for robust stability and/or robust performance. This choice necessitates a particular selection of excitation spectrum and data filter transfer function, recall Lemmata 4.2 and 4.1. With the original version of the Zangscheme (Zang *et al*, 1992, 1991), the identification was performed with only performance, as opposed to stability, considerations in mind. The original Zangscheme not only included a disturbance rejection agendum, but also reference tracking. Therefore the reference model determined the excitation spectrum applied during the identification experiment, and the model fitting is performed with a data filter as Lemma 4.1.

The controller enhancement step of the Zangscheme can be characterised in frequency domain terms as,

$$C_{i+1} = \arg\min_{C \in \mathcal{C}} \frac{1}{2\pi} \int_{-\pi}^{\pi} |\hat{F}|^2 \frac{|\hat{H}_{i+1}|^2}{|1 + C\hat{P}_{i+1}|^2} [1 + \lambda |C|^2] d\omega, \tag{7.6}$$

where $\hat{F}$ approximates the exact desired frequency weighting, F. The full order frequency weighting, F, as defined by (7.3), can be expressed in terms of spectral factors given by the achieved and designed closed loop sensitivity functions. That is,

$$F(z) = \left\{ \frac{H(z)[1 + C(z)\hat{P}(z)]}{\hat{H}(z)[1 + C(z)P(z)]} \frac{H(z^{-1})[1 + C(z^{-1})\hat{P}(z^{-1})]}{\hat{H}(z^{-1})[1 + C(z)^{-1}P(z^{-1})]} \right\}^{1/2}, \tag{7.7}$$

where $\{\cdot\}^{\frac{1}{2}}$ means to take the stable minimum phase spectral factor. Thus $F_{i+1}(e^{j\omega})$ satisfies,

$$F_{i+1}(e^{j\omega}) = \left| \frac{H(e^{j\omega})(1 + C_i(e^{j\omega})\hat{P}_i(e^{j\omega}))}{\hat{H}_i(e^{j\omega})(1 + C_i(e^{j\omega})P(e^{j\omega}))} \right|. \tag{7.8}$$

By considered criterion, (7.2), which is minimised during the design of the enhanced controller, C_{i+1}, it is evident that the closed loop signals $\{y_k^c,\ u_k^c\}$ used during the control design depend upon $(P, \hat{P}_{i+1}, C_{i+1})$. These closed loop signals are not synchronised with the signals that are used to generate estimated frequency weighting, $\hat{F}_i$, which depend upon $(P, \hat{P}_i, C_i)$, recall equations (7.2) and (7.8). The frequency weighting is a correction to make approximately a standard LQG disturbance rejection criterion take on the appearance of the criterion used to evaluate controller performance. Given that the frequency weighting cannot depend upon the future controller, C_{i+1}, then unless $\hat{P}_i$ and $\hat{P}_{i+1}$ are close, the frequency weightings applied in the minimisation of (7.2) will be inappropriate. Large discrepancies between $\hat{P}_i$ and $\hat{P}_{i+1}$ may still be accommodated through a frequency weighted controller. Typically it will be at the expense of guaranteed closed loop performance in the achieved closed loop system.

7.3 Decoupled Zangscheme Variant

As noted in the Section 7.1, this variant partially decouples the model adjustment and controller enhancement phases of the Zangscheme iterative design. The decoupling is achieved by modifying the controller enhancement expression such that the closed loop input-output signals used to estimate the frequency weightings for the controller design depend upon the current iteration's plant model, $\hat{P}_{i+1}$.

The $(i+1)$-th iteration of the decoupled Zangscheme variant involves the following steps :-

1. Perform a closed loop experiment with a fixed controller C_i acting upon the true plant P with an external excitation, r_k, added to the plant input, as in Figure 2.1, page 14, to generate a data set $\{y_k, u_k\}$ of length N.

2. Compute the data filter D_{i+1} as per equation (7.4).

3. With the data set $\{y_k, u_k\}$ identify $\hat{P}_{i+1}(\theta)$ using D_{i+1}.

4. Perform a closed loop simulation with the same fixed controller C_i acting upon the plant model $\hat{P}_{i+1}(\theta)$ as in Figure 2.2, page 25, to generate a data set $\{y_k^c, u_k^c\}$ of length N.

5. With the data sets from the experiment and simulation identify AR models of y_k, u_k, y_k^c, u_k^c to approximate, respectively, $\Phi_y^{\frac{1}{2}}, \Phi_u^{\frac{1}{2}}, \Phi_{y^c}^{\frac{1}{2}}, \Phi_{u^c}^{\frac{1}{2}}$.

6. Calculate the frequency weighting estimates $\hat{F}_1$ and $\hat{F}_2$.

7. Design a new frequency weighted feedback controller C_{i+1} based on $\hat{P}_i(z,\theta)$ and the identified signal spectra.

The controller enhancement criterion associated with the decoupled Zangscheme variant becomes,

$$C_{i+1} = \arg\min_{C\in\mathcal{C}} \frac{1}{N}\left[\sum_{k=1}^{N} \hat{F}^2(P,\hat{P}_{i+1},C_i)[(y_k^c(\hat{P}_{i+1},C))^2 + \lambda[u_k^c(\hat{P}_{i+1},C)]^2\right], \qquad (7.9)$$

An equivalent frequency domain characterisation is,

$$C_{i+1} = \arg\min_{C\in\mathcal{C}} \frac{1}{2\pi}\int_{-\pi}^{\pi} |\hat{F}|^2 \frac{|\hat{H}_{i+1}|^2}{|1+C\hat{P}_{i+1}|^2}[1+\lambda|C|^2]d\omega, \qquad (7.10)$$

where $\hat{F}$ approximates the minimum phase spectral factor,

$$F_{i+1}(e^{j\omega}) = |\frac{H(e^{j\omega})(1+C_i(e^{j\omega})\hat{P}_{i+1}(e^{j\omega}))}{\hat{H}_i(e^{j\omega})(1+C_i(e^{j\omega})P(e^{j\omega}))}|. \qquad (7.11)$$

Remark 7.3.1 The properties of the model adjustment phase in the decoupled Zangscheme variant remain as per the original Zangscheme.

Remark 7.3.2 The decoupled variant has been referred to by a gaggle of names in previous publications. The decoupled variant was called the two-stage refinement in Partanen and Bitmead (1993b), and the indirect Zangscheme iterative design in Partanen and Bitmead, (1995)[1]. In this thesis, the terms, *two-stage* and *indirect*, also describe closed loop identification. To avoid reader confusion, the term *decoupled*, applies in this thesis to the Zangscheme variant which may, elsewhere, have been called the two-stage, indirect, or two-stage indirect variant.

Remark 7.3.3 In the original Zangscheme, a single iteration produces $\hat{P}_{i+1}, C_{i+1}$ from weightings which depend upon $P, \hat{P}_i, C_i$. The decoupled Zangscheme variant uses $\hat{P}_{i+1}$ instead of $\hat{P}_i$ to compute the frequency weightings for the controller design, and thus better aligns the algorithm and should reduce the scope for controller misadjustment. Tying this to previous comments about cautious controller enhancement, it is clear that

[1]The deliberate name alterations are there to keep fly-by-nighters off the scent.

appropriately updated and regulated frequency weightings are important to limit gross changes to the controller parameters.

Remark 7.3.4 The decoupling of the model adjustment and controller enhancement is only partial since the data filter, D_{i+1}, used to frequency weight the identification still depends upon $\hat{P}_i, C_i$ rather than on $\hat{P}_{i+1}, C_i$. To further decouple the model adjustment and controller enhancement steps the data filter must be parametrized in terms of the plant model, $\hat{P}_{i+1}$, which is yet to be identified. Clearly, this a non-standard identification problem which may be solved using non-linear optimisation methods (Dennis and Schnabel, 1983). This is the subject of ongoing research. To be able to use standard system identification methods, the data filter, D_{i+1}, must be specified before the plant model, $\hat{P}_{i+1}$, can be fitted. Clearly, the plant model, $\hat{P}_{i+1}$, is unavailable for the design of the data filter, D_{i+1}. To overcome this problem, the following iteration, with iteration index j, can be performed repeatedly as part of the model adjustment step.

1. Compute the initial data filter, $D_{i,j}$, according to

$$D_{i+1,j} = \frac{\hat{H}_{i,j+1} G_i}{1 + C_i \hat{P}_{i+1,j}(\theta)}, \tag{7.12}$$

2. Using the data set $\{y_k, u_k\}$ obtained by a closed loop identification experiment in Step 1 of the decoupled Zangscheme variant, and the data filter, $D_{i+1,j}$, identify the updated plant model, $\hat{P}_{i+1,j}$.

The data filter and model fitting iteration is repeated until the updated parameters of the plant model, $\hat{P}_{i+1,j}$, have converged. Unfortunately, with such an iterative adjustment plant model parameter convergence is application dependent. An analogous approach is used by de Callafon *et al* (1994) in the identification of normalised coprime factors subject to a parametrization constraint (recall Section 3.6). This iteration will typically complicate the algorithm (Zang *et al*, 1995), therefore, it not generally performed in, either, the original Zangscheme or the decoupled variant.

Remark 7.3.5 It has been suggested in some quarters, that a single iteration of the Zangscheme should also include repeated frequency weighting estimation and the controller minimisation performed continually until the frequency weightings depend upon the final controller, C_{i+1}, and not the current controller, C_i, as it does in (7.9). This innovation would, like the data filter iteration described in the previous remark, perhaps unnecessarily complicate the decoupled Zangscheme algorithm. However, by forgoing the model adjustment step, the frequency weighting and control design iteration can be continually iterated. This observation provides motivation for the direct Zangscheme variant considered next.

7.4 Direct Zangscheme Variant

The partial decoupling of the identification and control design phases that results in the decoupled variant of the original Zangscheme allows the proposition of a direct variant in which the model adjustment phase has been completely removed from the iterative design. This modification permits controller enhancement without the attendant need for plant model adjustment, hence forgoing the necessity to conduct an identification experiment.

With the direct Zangscheme variant, the controller is updated whilst the model is kept constant. This is almost a dual analogy to indirect adaptive control (Åström and Wittenmark, 1989), during which the plant model is updated by online recursive identification of experimental data, whilst the control law is fixed.

The controller enhancement minimisation for the direct Zangscheme variant is

$$C_{i+1} = \arg\min_{C \in \mathcal{C}} \frac{1}{N} \left[\sum_{k=1}^{N} \hat{F}^2(P, \hat{P}_0, C_i)[(y_k^c(\hat{P}_0, C))^2 + \lambda[u_k^c(\hat{P}_0, C)]^2 \right], \tag{7.13}$$

where P_0 is the initial and only model of the plant. The model, $\hat{P}_0$, is never adjusted. In order to maintain closed loop stability, the relative plant model mismatch associated with initial plant model, $\hat{P}_0$, must be small in those frequency bands where the complementary sensitivity is large.

Remark 7.4.1 When $\hat{P}_0 = P$, Zang *et al* (1992) demonstrate that the original Zangscheme accommodates disturbance model inaccuracy ($\hat{H} \neq H$) in one iteration.

With the direct variant, the frequency weightings have to account for the entire closed loop model mismatch, whereas with the original Zangscheme and its decoupled variant the plant model would pick up some of this mismatch. Lemma 4.2 indicates that large frequency weightings might be detrimental to robust stability. In practice, a composite iterative design methodology is adopted. This composite approach employs a single iteration of the decoupled variant followed by multiple iterations of the direct variant until no performance enhancement results. This approach is similar to the IMC iterative design where a model re-identification is performed only when the model can no longer adequately deliver a controller which meets the performance specifications.

7.5 Simulation Example

In order to compare the various implementations of the Zangscheme the following computer simulation has been undertaken.

The true plant under investigation is *7th* order of the following form,

$$y_t = P(z)u_t + v_t = \frac{B(z)}{A(z)}u_t + H(z)e_t, \tag{7.14}$$

where the coefficients of the polynomials $A(z), B(z)$, represented in vector form as a and b, are respectively

$$\begin{aligned} a &= [1\ \ 0.0049\ \ -0.0848\ \ -0.1953\ \ 0.1450\ \ -0.0159\ \ -0.0505\ \ 0.0145] \\ b &= [0\ \ 0.5\ \ 1.5059\ \ 0.8575\ \ 0.0897\ \ 0.5463\ \ 0.0738\ \ 0.0002]. \end{aligned}$$

This is a stable and nonminimum phase plant with unit delay. The disturbance filter is high pass with a transfer function,

$$H(z) = \frac{1 - 0.975z}{1 + 0.1z}.$$

Figure 7.1 gives the frequency response for the true plant and the true disturbance. Figure 7.1 includes the initial plant model P_0 which faithfully captures the low pass nature of the true plant. An initial non-frequency weighted LQG controller, C_0, has been designed on the basis of the initial model $\hat{P}_0$.

The following iterative designs were conducted over 8 iterations, starting with the same initial plant model $\hat{P}_0$ and initial controller C_0,

- original Zangscheme iterative design.
- decoupled Zangscheme variant iterative design.
- direct Zangscheme variant iterative design.

- a composite Zangscheme iterative design uses the decoupled Zagnscheme variant during the first iteration and the direct variant for the remaining iterations.

The iterative designs with a model adjustment phase identify 3rd order plant models and 1st order disturbance models using a Box-Jenkins algorithm to minimise sum-squared filtered prediction errors. Uniformly distributed white noise excitation of variance 0.3 was used to excite the plant to facilitate closed loop identification. A low penalty on control action, i.e. $\lambda = 0.01$, was assigned during the design. Figure 7.2 gives the performance for the achieved closed loop system for the four iterative designs listed above. The performance of the truly optimal controller designed on the basis of exact plant and disturbance knowledge is also plotted in Figure 7.2 for comparative purposes.

Remark 7.5.1 Since the plant is *7th* order and the disturbance is *1st* order, the optimal LQG controller will be *8th* order. As the Zangscheme uses a *3rd* order plant model, *1st* order disturbance model, and a *3rd* order AR model estimate for the single frequency weighting, the resultant frequency weighted LQG controller will be *7th* order. Therefore, the Zangscheme controller is of a complexity less than the optimal controller.

Remark 7.5.2 The model adjustment phase of the first iteration in both the original Zangscheme and its decoupled variant identifies the same plant and disturbance models, $(\hat{P}_1, \hat{H}_1)$, for a common initial plant, $\hat{P}_0$, initial disturbance, $\hat{H}_0$, and an initial controller, C_0. Therefore, the model mismatch in the first iteration is identical and independent of the available Zangscheme implementations that include a model adjustment phase. The identified plant model, $\hat{P}_1$, shown in Figure 7.1 is a better approximation of the true plant in the high frequency band than the initial plant model, $\hat{P}_0$. Figure 7.2 confirms that the reformed frequency weighting estimate of the decoupled Zangscheme variant produces a better performing controller more quickly than the original Zangscheme for the same initial plant model mismatch.

Remark 7.5.3 In the limit, both the original Zangscheme and the decoupled Zangscheme variant give the same achieved performance.

Remark 7.5.4 Although the direct Zangscheme variant produces some initial reduction in the achieved performance, refer Figure 7.2, the overall improvement is constrained by the

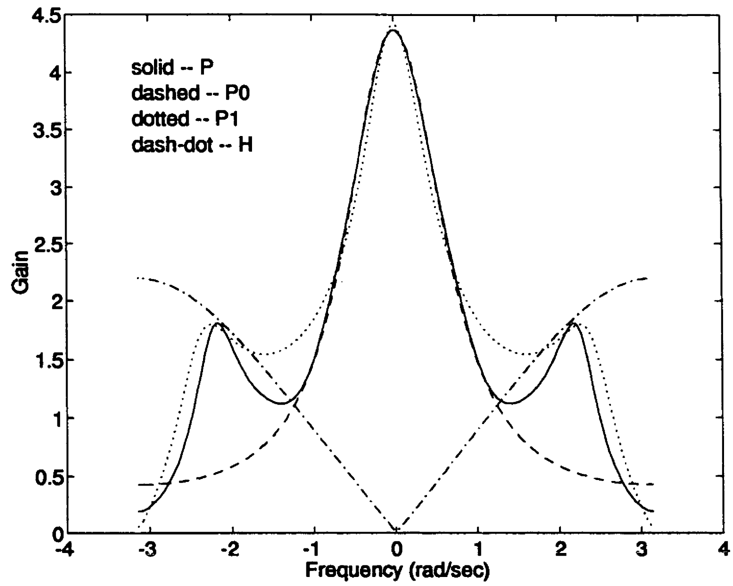

Figure 7.1: Bode plots of the true plant, P, true disturbance, H, initial plant model, $\hat{P}_0$, and the identified plant $\hat{P}_1$ for the iterative designs with model adjustment.

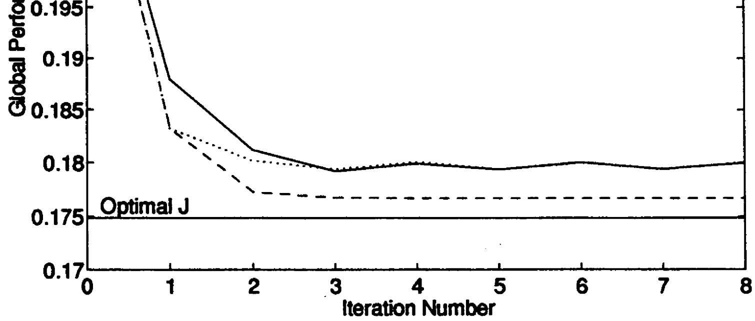

Figure 7.2: Achieved Performance J^{ach} of the enhanced controllers for various iterative designs.

poor nature of the initial plant model, $\hat{P}_0$, at high frequencies. For this reason a composite iterative scheme which includes a model adjustment phase for the first iteration only, was peformed. The achieved performance of the enhanced controllers from the composite iterative design is better than the corresponding controllers from the other Zangscheme iterative designs, as is indicated by Figure 7.2. The practical implication of the composite Zangscheme results is that a closed loop identification experiment with suitably chosen plant excitation signal need only be performed occasionally. Furthermore, this result suggests that the model adjustment phase of the original and the decoupled Zangscheme iterative designs degrade the achieved performance during the later iterations. That is, the models are not adjusted in an optimal direction with respect to control design. This example provides anecdotal support for the observation made by de Bruyne and Gevers (1994), that the optimal restricted complexity plant model cannot always be identified.

Remark 7.5.5 With all versions of the Zangscheme, most of the performance enhancement resulted during the first 2-3 iterations. This reinforces the notion that the iterative designs are not meant be iterated forever, and that only a few iterations are required before the relative magnitude of the performance enhancement is reduced to such a degree that further iterations can no longer be justified.

7.6 Cautious Controller Enhancement

The solution to the frequency-weighted LQ performance objective (4.4) is an algebraic one involving Riccati and Lyapunov equations. Therefore, the designer has very little influence on the resulting difference between the enhanced and the existing controllers. Scalable frequency weightings are a mechanism by which cautious controller enhancement can be effected using the Zangscheme. This feature slows the rate of controller modification, particularly with the direct Zangscheme variant which uses a fixed plant model. Application of the decoupled Zangscheme variant with scalable frequency weightings produces a less cautious adjustment to the controller parameters than that achieved using the direct Zangscheme variant, since plant model parameters are also adjusted.

Remark 7.6.1 Cautious controller design should not be confused with cautious controller enhancement. Recall from Definition 2.7.2, that a cautious controller results from a control design in which the uncertainty of the model parameter estimates is explicitly taken into account. Whereas, with cautious controller enhancement, the term cautious refers to the relative magnitude of the adjustment to the existing controller parameters.

The effect of a frequency weighting F can be scaled, with respect to unity magnitude, by including a user adjustable parameter, $\delta \in \Re(0,1)$, into the frequency weight computation, that is,

$$F = \frac{\delta\Phi_y^{\frac{1}{2}} + (1-\delta)\Phi_{y^c}^{\frac{1}{2}}}{\Phi_{y^c}^{\frac{1}{2}}}. \tag{7.15}$$

Remark 7.6.2 Severe frequency weighting diminution, that is, $\delta = 0$, effects no frequency weighting, whilst $\delta = 1$ implements the full frequency weighting.

Remark 7.6.3 Small values of δ result in the cautious enhancement of controller parameters, similar to the iterative schemes of Lee *et al* (1993a), and Schrama *et al* (1992a).

Remark 7.6.4 Since the frequency weightings are derived from disturbance driven closed loop signals, the frequency weightings are a measure of the difference in closed loop performance between the achieved and designed closed loops. As such the frequency weightings are performance oriented modifiers to a standard LQG controller design (recall Remark 4.2.2). During the controller design stage of the Zangscheme, frequency weightings potentially offer performance enhancement, but sometimes at the expense of closed loop stability. Lemma 4.2 indicates that gradual controller enhancement through scalable frequency weightings is one mechanism available to the user to tailor the Zangscheme controller design for robust stability.

Remark 7.6.5 For many industrial processes, like the sugar cane crushing mill, open loop stable controllers are desired, recall Remark 5.3.10. In the case of reduced complexity modelling of a complex industrial process, frequency weightings with large deviations from unity are to be expected. Typically, without scaling the frequency weighting, the result of the controller design is a new enhanced controller, C_{i+1}, which is significantly different from the existing open loop stable controller, C_i. The open loop stability of the C_i may disappear with C_{i+1}. Scalable frequency weightings also allow the designer freedom to effect an open loop stable control solution during the application of the Zangscheme iterative design. Open loop stable LQG controllers can also be designed using a particular selection of weighting and covariance design matrices during a standard non-frequency weighted LQG design (Halevi, 1994). The same applies for a frequency weighted LQG controller since the design can be transformed into one which uses standard LQG methods.

7.7 The Revised Zangscheme

In order to overcome some of the shortcomings of the original Zangscheme iterative design, i.e.

- a controller design with scope for misadjustment of controller parameters,
- a not-so-cautious controller enhancement,

a revised version is proposed. The revised algorithm involves the following cycle :-

1. multiple iterations of the direct Zangscheme variant until achieved closed loop performance is no longer improved.
2. a single iteration of the decoupled Zangscheme variant during which an updated plant model is identified.

Remark 7.7.1 Scalable frequency weightings are now standard in both variants.

Remark 7.7.2 Depending upon the size of the model adjustment effected during the application of the decoupled Zangscheme variant in the second step of the revised Zangscheme, it may become necessary to avoid applying any frequency weightings during the controller design in order to obtain an open loop stable controller. This was the case during the application of the revised Zangscheme to the sugar cane crushing process, refer Remark 8.3.5.

7.8 Frequency Weighted Controller Design

The Zangscheme differs from merely a succession of prediction error identifications and LQG control designs, through the estimation of frequency weightings which are used to modify the controller design criterion. Whether considering the achieved or designed closed loop systems, analytic expressions for the difference between the actual measured closed loop output signal and the output of the Kalman predictor part of an LQG controller can be written. Furthermore, this signal is internally constructed in the controller, and hence is available for analysis. In the case of the achieved closed loop system such a signal is classified as the **achieved predicted difference**. Whilst, in the case of the designed closed loop system, this signal is described as the **designed predicted difference**. Again the analysis which follows applies to SISO systems. An equivalent analysis for multivariable systems is not yet available.

Consider the output, y_k, of the achieved closed loop system with the plant and disturbance pair, (P, H), and a frequency-weighted LQG controller, C, which results from a standard non-frequency-weighted controller using system model estimate, $(\hat{\hat{P}}, \hat{\hat{H}})$, where $\hat{\hat{P}} = P$ and $\hat{\hat{H}} = F\hat{H}$ (recall equation (4.6)). F is the frequency weighting defined in (7.3). Recall from Section 4.2 that a standard non-frequency-weighted design on $(\hat{\hat{P}}, \hat{\hat{H}})$ delivers an optimal controller, $\bar{C}$, which is the minimising solution to the frequency weighted LQG criterion, (7.2), i.e. $C = \bar{C}$. The predicted difference signal associated with the achieved closed loop is defined as,

$$\nu_k^{ach}(P, \hat{\hat{P}}, H, \hat{\hat{H}}) \triangleq y_k(P, H) - \hat{y}_{k|k-1}(\hat{\hat{P}}, \hat{\hat{H}}), \tag{7.16}$$

where $\hat{y}_{k|k-1}$ is a prediction of the plant output, y_k, using estimated models, $(\hat{\hat{P}}, \hat{\hat{H}})$, and past values of the input-output signals, $\{y_k, u_k\}$, that is,

$$\hat{y}_{k|k-1} = \hat{\hat{H}}^{-1}\hat{\hat{P}}u_k + [1 - \hat{\hat{H}}^{-1}]y_k. \tag{7.17}$$

The designed predicted difference associated with the output, y_k^f, of a closed loop system with the plant and disturbance pair, $(\hat{\hat{P}}, \hat{\hat{H}})$, and a standard non-frequency-weighted LQG controller, $\bar{C}$, designed using system model estimate, $(\hat{\hat{P}}, \hat{\hat{H}})$, is defined as,

$$\nu_k^{des} \triangleq y_k^f(P, H) - \hat{y}_{k|k-1}^f(\hat{\hat{P}}, \hat{\hat{H}}), \tag{7.18}$$

where $\hat{y}_{k|k-1}^f$ is the one-step-ahead prediction the plant model output, y_k^f, that is,

$$\hat{y}_{k|k-1}^f = \hat{\hat{H}}^{-1}\hat{\hat{P}}u_k^f + [1 - \hat{\hat{H}}^{-1}]y_k^f. \tag{7.19}$$

Figure 7.3 shows the designed closed loop system, $(\hat{\hat{P}}, \hat{\hat{H}}, \bar{C})$.

Remark 7.8.1 Since the LQG controller design is based upon system model estimates,

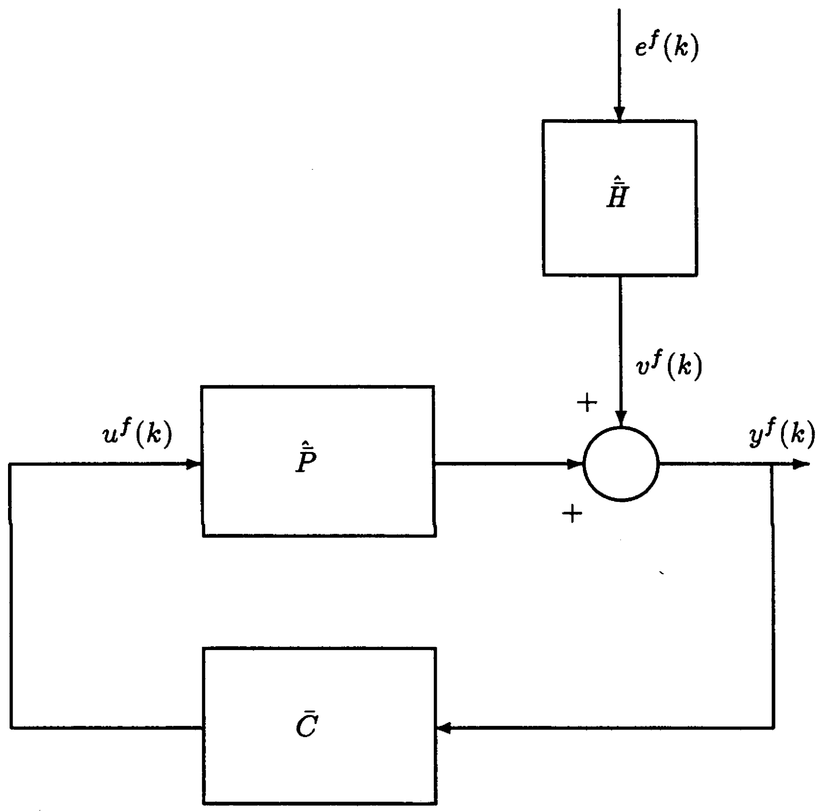

Figure 7.3: Designed closed loop system featuring model estimates, $(\hat{\bar{P}}, \hat{\bar{H}})$.

$(\hat{\hat{P}}, \hat{\hat{H}})$, the one-step-ahead prediction, $y^f_{k|k-1}$, is therefore the optimal least squares estimate of the design closed loop output, y^f_k. Hence, the designed predicted difference, ν^{des}_k, is the Kalman predictor innovations process which, in this instance, is also equivalent to the one-step-ahead prediction error associated with $y_{k|k-1}(\hat{\hat{P}}, \hat{\hat{H}})$.

Remark 7.8.2 The achieved predicted difference, ν^{ach}_k, will not necessarily correspond to the Kalman predictor innovations process nor to a one-step-ahead prediction error. This is because the plant and disturbances are unknown, and therefore the predicted output, $\hat{y}_{k|k-1}$, which is determined according to models, $(\hat{\hat{P}}, \hat{\hat{H}})$, and past values of the input-output data, $\{y_k, u_k\}$, may not necessarily produce the optimal least squares prediction of the plant output, y_k.

It is well known that with Kalman predictors, their innovations process will be white when the filter is implemented on the exact same system for which was it has been designed (Kwakernaak and Sivan, 1972). Therefore, when an LQG controller, which by definition contains a Kalman predictor, is implemented on systems that can only be approximated, the whiteness of the achieved predicted difference, ν^{ach}_k, can be used to gauge the suitability of a particular design and any modifications made to the design process. The notion of isolating the predicted difference signals and examining their whiteness as a mechanism for ascertaining the suitability of a particular design paradigm is not new. It has been considered by Liu and Anderson (1986) with respect to choosing between a suitable coprime representation, i.e left or right, for controller reduction in which the discrepancy between the full order closed loop systems and its reduced order counterpart is minimised. In this section, the achieved predicted difference signal is examined to provide additional justification for undertaking frequency weighted LQG design.

Theorem 7.1 *Consider the Zangscheme iterative design, in which the frequency weighted LQG controller, C, in class of controllers, $\mathcal{C}$, is obtained by minimising the criterion,*

$$\lim_{N\to\infty} \frac{1}{N} E\left[\sum_{k=1}^{N} \hat{F}^2[(y^c_k)^2 + \lambda(u^c_k)^2]\right], \tag{7.20}$$

where $\{y^c_k, u^c_k\}$ are signals from the designed closed loop system depicted in Figure 2.2, *page 25, and F is the frequency weighting defined as,*

$$F = \left\{\frac{\Phi_y}{\Phi_{y^c}}\right\}^{\frac{1}{2}} = \left\{\frac{\Phi_u}{\Phi_{u^c}}\right\}^{\frac{1}{2}}.$$

Then, the predicted difference, ν_k^{ach}, associated with the achieved closed loop system, (P, H, C), is given by,

$$\nu_k^{ach} = T(z)e_k, \tag{7.21}$$

where e_k is a white noise process of unit variance which drives the achieved closed loop system, refer Figure 2.1, page 14, and $T(z)$ is a stable all-pass transfer function.

Proof

Recall from above, that the controller, C, which minimises the frequency weighted LQG criterion, (7.20), is the same as the controller, $\bar{C}$, obtained by minimising the standard non-frequency-weighted LQG criterion,

$$\lim_{N\to\infty} \frac{1}{N} E\left[\sum_{k=1}^{N} \hat{F}^2[(y_k^f)^2 + \lambda(u_k^f)^2]\right], \tag{7.22}$$

where $\{y_k^f, u_k^f\}$ are signals from the designed closed loop system, $(\hat{\bar{P}}, \hat{\bar{H}}, \bar{C})$, depicted in Figure 7.3. When the standard non-frequency-weighted controller, $\bar{C}$, is implemented in the achieved closed loop as the frequency weighted controller, C, equation (7.17) gives the output of the Kalman predictor associated with C. Substituting for $\hat{\bar{P}} = \hat{P}, \hat{\bar{H}} = F\hat{H}$ in (7.17) yields,

$$\hat{y}_{k|k-1} = F\hat{H}^{-1}\hat{P}u_k + [1 - F\hat{H}^{-1}]y_k. \tag{7.23}$$

Substituting the control law, $u_k = -Cy_k$, gives,

$$\hat{y}_{k|k-1} = [1 - (1 + C\hat{P})F\hat{H}^{-1}]y_k. \tag{7.24}$$

Substituting the minimum phase spectral factor associated with the frequency weighting, F, recall equation (7.11), gives,

$$\begin{aligned}
\hat{y}_{k|k-1} &= [1 - (1 + C\hat{P})\frac{\hat{H}(1 + CP)}{H(1 + C\hat{P})\hat{H}}]y_k, \\
\hat{y}_{k|k-1} &= [1 - \frac{1 + CP}{H}]y_k.
\end{aligned} \tag{7.25}$$

Hence, the achieved predicted difference signal can be written as,

$$\nu_k^{ach} = \frac{1+CP}{H} y_k. \tag{7.26}$$

The output, y_k, of the achieved closed loop system driven by a white noise process with unit variance, e_k, is

$$\begin{aligned} y_k &= \frac{H}{1+CP} e_k, & (7.27) \\ &\triangleq S e_k & (7.28) \end{aligned}$$

where S is stable. Therefore,

$$\begin{aligned} \nu_k^{ach} &= \frac{H(1+CP)}{H(1+CP)} e_k, & (7.29) \\ &\triangleq T(z) e_k & (7.30) \end{aligned}$$

where $T(z)$ is a stable all-pass transfer function[2]. An alternative proof based on state variable realisations is given in Appendix D. ■

Theorem 7.1 shows that the effect of the frequency weighting in the Zangscheme iterative design is to whiten the difference between the measurable output, y_k, and the Kalman predictor output, $\hat{y}_{k|k-1}$, for the achieved closed loop. In this sense, the frequency weighting, F, attempts to maintain the designed closed loop performance when the frequency weighted LQG controller is implemented in the achieved closed loop system[3]. The result of Theorem 7.1 restates that the intention of the frequency weighting correction to the LQG controller design in the Zangscheme iterative design, is to bring closer together the different closed loop systems in which controller is designed, and in which controller performance is evaluated.

Remark 7.8.3 In practice, the whitening effect on the achieved predicted difference signal due to the frequency weighted controller is approximate, since estimated non-exact frequency weightings are used in the controller design.

[2] $T(z)$ is written as an all-pass transfer function. Since the phase of H is arbitrary and e_k is inaccessible, $T(z) = 1$ can also be written.

[3] Beyond this no claim is made concerning the consequences of whitening ν_k^{ach}.

Remark 7.8.4 If there exists a mismatch between the achieved and designed closed loops systems, i.e. $F \neq 1$ for some $\omega \in [-\pi, \pi)$, then a standard non-frequency-weighted LQG controller design performed on $(\hat{P}, \hat{H})$, i.e.

$$C^{lqg} = \arg \min_{C \in \mathcal{C}} \frac{1}{N} \left[\sum_{k=1}^{N} [(y_k^c)^2 + \lambda (u_k^c)^2] \right], \tag{7.31}$$

produces a controller, C_{lqg}, which when implemented on the achieved closed loop, (P, H), in general will not attempt explicitly to whiten the achieved predicted difference signal, ν_k^{ach}. In this case, the achieved predicted difference signal will be characterised by,

$$\nu_k^{ach} = \frac{1 + C^{lqg} \hat{P}}{\hat{H}} y_k. \tag{7.32}$$

Remark 7.8.5 When a frequency weighted LQG design is attempted on the system, $(\hat{P}, \hat{H})$, with $F \neq 1$ for some $\omega \in [-\pi, \pi)$, the predicted difference associated with the closed loop system, $(\hat{P}, \hat{H})$, will not be white. This observation is an obvious consequence of the fact that a frequency weighted LQG controller design for $(\hat{P}, \hat{H})$ does not necessarily correspond to a standard non-frequency-weighted design on $\hat{P}, \hat{H}$. This result suggests that designing a controller, solely, on the basis of inexact models, $(\hat{P}, \hat{H})$, of the true system is not entirely appropriate. By using information contained in readily available closed loop input-output signals to estimate frequency weightings which are then used as corrections in a controller design, the designer is deliberately employing *a posteriori* information to influence appropriately the direction of the next controller adjustment. This reaffirms that the Zangscheme iterative design includes an adaptive agendum. However, it should not be forgotten that the frequency weighting is a performance oriented correction to a standard controller design, and large frequency weightings may have detrimental consequences for stability, recall Section 4.2.

Remark 7.8.6 Zang *et al* (1992) have shown for an exact plant description $\hat{P} = P$ and an inexact disturbance description $\hat{H} \neq H$, the Zangscheme iterative design will deliver the truly optimal controller in one iteration. With an inexact plant description $\hat{P} \neq P$ and an exact disturbance description $\hat{H} = H$, the Zangscheme iterative design will achieve approximately the same level of disturbance rejection for the achieved and designed closed loop systems. This section could been seen to generalise these findings for the case of inexact plant and disturbance knowledge, i.e $\hat{P} \neq P, \hat{H} \neq H$, although the performance implications of these findings are unclear as yet.

Remark 7.8.7 Liu and Anderson (1986) undertake controller reduction with a view to also preserving the whiteness of the closed loop innovations process. Hence, there exists strong evidence of a linkage between the Zangscheme iterative design and controller reduction. The fact that the controller orders are maintained low by these methods is further contact between the two approaches to restricted complexity controller design. The essential difference between the two approaches is that the Zangscheme makes explicit use of operational data in the design of restricted complexity controllers.

Remark 7.8.8 If the frequency weighting are scaled prior to the controller design, then the tendency of the frequency weighted controller to whiten the predicted difference signal in the achieved closed loop system will also be scaled accordingly.

The entire implications of the whitening of achieved predicted difference signal, ν_k^{ach}, are not yet apparent, as indeed they are not in Liu and Anderson (1986). Future work could concentrate on a formal connection between iterative controller design using closed loop data and restricted complexity controllers. The unifying theme is that the controllers are chosen to reflect their performance in the achieved closed loop system.

Remark 7.8.9 Optimal minimum variance control of minimum phase single delay systems can be verified by examining the whiteness of the process output (Åström and Wittenmark, 1990, Åström, 1970). Whiteness testing is used by statistical process control practitioners to evaluate process performance and to detect negative effects on the process (Wetherill and Brown, 1991). No claims are made in thesis regarding the optimality of an achieved closed loop system with a white predicted difference signal. Nevertheless, given the optimality results from minimum variance control and whiteness testing in statistical process control, further investigation on the whiteness of the achieved predicted difference signals and the optimality of frequency weighted LQG controller design with respect to the achieved closed loop system is well warranted.

7.9 Simulation Example

The simulation example is as per Section 7.5. The results presented in this Section apply to controllers derived from the composite Zangscheme iterative design. Figure 7.4 plots the frequency response of the transfer function, $T(z)$, which relates the white noise process, e_k, to the predicted difference signal, ν_k^{ach}, in the achieved closed loop system for the first three iterations of the design. The solid line in Figure 7.4 gives the frequency response of the transfer function, $T(z)$, derived using knowledge of the full order optimal LQG controller (designed using the true plant and the true disturbance). It comes as no surprise that in this instance, the predicted difference signal, ν_k^{ach}, is white. The initial iteration is based upon an achieved closed system with an initial non-frequency weighted LQG controller C_0 derived from an initial plant model $\hat{P}_0$ which captures only the low pass nature of the true plant, hence the predicted difference signal, ν_k^{ach}, for the initial achieved closed loop is not white. After two iterations Figure 7.4 shows the iterative scheme has delivered an LQG controller which has whitened the achieved predicted difference signal, ν_k^{ach}. Numerical approximations have given an imperfect pole/zero cancellation for the almost all-pass transfer function, T, near dc after the second iteration. This is not significant due to the near zero disturbance energy around dc. Further iterations did not alter the frequency response of the transfer function, T.

7.10 Chapter Conclusions

The revised Zangscheme iterative design incorporates many attractive features of the Delft and IMC iterative designs. Namely, cautious controller enhancement and occasional model identification. These features add an element of robustness into the Zangscheme by reducing the magnitude of controller modification. Therefore, the revised Zangscheme provides a gradual solution to controller refinement.

The use of operational data to direct, either, the model adjustment or controller enhancement aspects of iterative control design is one of the major themes of thesis. The frequency weighted LQG control design used in the Zangscheme takes *a posteriori* closed loop information which allows the designer to attempt control design with respect to a system model which better approximates the unknown system. From a theoretical perspective, the Zangscheme uses the *a posteriori* information in a manner appropriate to the

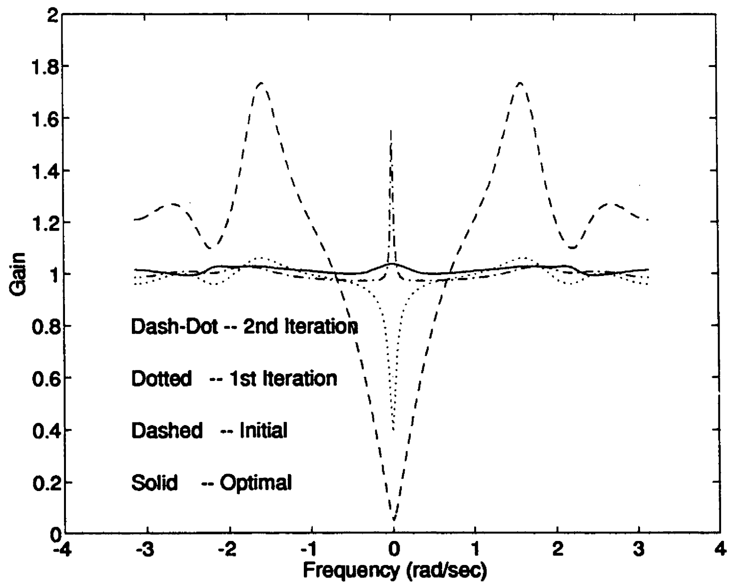

Figure 7.4: Bode plot of the Transfer Function, $T(z)$, relating the white noise process, e_k, to the predicted difference signal, ν_k^{ach}, associated with the achieved closed loop system.

control design objective.

Having completed the theoretical treatment of controller refinement, the next chapter examines the application of the Zangscheme iterative design to controller refinement for the sugar cane crushing process.

Chapter 8

Application of the Revised Zangscheme Iterative Design to the Sugar Cane Crushing Mill

8.1 Chapter Motivation

The sugar cane crushing process is typical of many difficult-to-control industrial processes in that an accurate dynamical model of the process and disturbances acting upon it does not exist. Fortunately, approximate models which adequately describe the process dynamics for the purposes of control design can be identified. For processes like sugar cane crushing, the difficulty in obtaining such models is compounded by the requirement that the identification be performed with closed loop data. Many of the difficulties associated with closed loop identification can be overcome by using a systematic approach, as was presented in Chapter 6 for the crushing process. Although unmodelled process non-linearities are a major issue, by maintaining low controller order during a linear control design, then potentially, the extent of pejoration in closed loop process performance attributable to the unmodelled process non-linearites is reduced. Despite the difficult-to-control nature of the sugar cane crushing process, the revised Zangscheme iterative identification and control design has been successful in enhancing closed loop process performance. This Chapter reports on the application outcome.

The sugar cane crushing process application results presented in this chapter compare the performance of LQG controllers culminating from the revised Zangscheme iterative design with that achieved using the existing PID controllers. The PID controllers are considered to be well tuned as the result of *ad hoc* adjustments made over many years. Although the LQG controllers were fitted with non-linear gain modifiers, the PID controllers operate with similar modifications, e.g. saturating rate limiters, gap detection logic.

All of the LQG controllers presented in this tome were sufficiently robust to replace the traditional decentralised PID control systems and to gain plant operator acceptance. The graphical results presented in this chapter represent the typical performance of the controllers during a particular crushing season. The histograms give an indication of the effectiveness of the regulation control. The mean and standard deviation (std) of each histogram distribution is given. Provided the histogram mean is close to the proces setpoint, small histogram standard deviations are indicative of good regulatory control. The time length of the controller trials is sufficiently long to ensure that the crushing process is subjected to the large variations in the physical properties of the incoming cane. The comparisons are made using data from the same time of day, since factory operations dictate that cane from particular districts, and therefore having approximately similar statistical variability, will be processed at approximately the same time every day.

Remark 8.1.1 With regard to the graphical plots comparing various LQG and PID performances, it should be noted that the controllers designations which appear within the graphical plots may in some cases appear to be in direct conflict with the controller described in the figure caption below the plot. Within the graphical plots the controller naming convention is different to the designations used in the thesis text. The designations within the plots were used during the controller trials when the graphical plots were produced. Unfortunately, with the software package which produces the graphical plots it is not possible to save the plots. The only way in which the figures can be replotted is by retrieving the data from archival disks. This is not always possible as some of the data prior to the 1994 crushing season is no longer available. Therefore, the reader should note that the controller designation given in the figure caption of the graphical plots are consistent with the controllers described in the text.

8.2 Seasonal and Regional Factors affecting Process Performance

Before presenting the application results, the impact of seasonal and regional factors which ultimately determine the level of achievable process performance is discussed.

In general, controller performance should be repeatable from one crushing season to the next. Degradation in controller performance from one crushing season to the next can be mostly attributed to a change in the nominal weather patterns under which each crushing season's sugar cane crop is grown. Depending upon the particular crushing season, this can result in a significant increase in the tonnage of harvested sugar cane with physical characteristics which are detrimental to, not only, the closed loop performance of the individual crushing units within a milling train, but also to the overall extraction performance of the milling train through which this cane is crushed.

The extent of deterioration in process performance due to the weather conditions which have an adverse affect on the physical properties of the sugar cane for milling, maybe further compounded when this variation in the climate is coupled with an increase in harvested tonnage from expansion districts. Typically in the Herbert River Valley sugar cane growing region, the soils of the major expansion districts are more marginal for the purposes of growing sugar cane than the soils of the traditional growing areas. Even without the intervention of less-than-ideal weather conditions, canes grown on poorer soilers, in general, affect the closed loop performance of a crushing process in a detrimental manner.

The impact of weather and soil conditions on the process feedstock are extremely difficult to take into account in a formulating a description of the process disturbances for the purpose of controller design. Therefore, these factors are not accounted for in the controller design. The use of operational process data to update a successful controller design, gives the user some scope for adjusting the controller in accordance with current operating conditions.

In the Herbert River valley, the cane growing region considered in this thesis, over 99% of the sugar cane sent to the mill for processing has been harvested green. In other growing regions, it may well be that 99% of the cane supplied to the mill has been burnt prior to harvesting, e.g. Burdekin River valley. Farmers in accordance with individual farm management policy determine whether the cane is harvested green or burnt. An assessment of the *mill-ability* of green and burnt cane is yet to be conducted.

8.3 Application Results

8.3.1 Height Regulation

Although the existing chute height/turbine speed PI loop regulates the chute height, tighter height regulation could be realised with LQG control. With tighter height regulation, the chute height set-point could be increased to derive a torque benefit through further compaction of the bagasse, without increasing the probability of feed chute overflows.

Tighter height control was achieved on A2 and A3 crushing mills by replacing the chute height/turbine speed PI controller with a corresponding LQG controller. A comparison of the PID versus LQG chute regulation results for the A3 milling unit (the more difficult to control) are shown in Figure 8.1. With LQG regulation of the chute height, a significantly higher set-point could be selected than with PID control.

Interestingly, the direct iterative design method of Hjalmarsson *et al*, (1995, 1994b, 1994c), recall Remark 2.8.4, used to minimise an LQG height control objective, (5.2), delivered after one iteration a direct (non-model-based) LQG height controller which possessed a step response remarkably similar to that of the model-based LQG height controller. Refer Figure 8.2. Further iterations of the Hjalmarsson direct iterative design did not produce significantly different height controllers. The difference between the steady-state component of the step responses is attributed to different mill roller distance settings. The two height controllers were trialled during separate crushing seasons, and since the factory throughput requirements depend upon the size of the projected sugar cane harvest, the mill rollers settings are altered accordingly at the start of each crushing season. Mill roller settings for various crushing seasons are given in Appendix E. This direct control design method is not yet available for multi-variable systems.

Although, the LQG controller permitted the operation of the crushing mills with higher chute height levels, a corresponding improvement in the torque did not eventuate. This is due to the multi-variable nature of the process. By applying a two loop decentralised control strategy as in Figure 5.1, the effect of any coupling between the two loops is

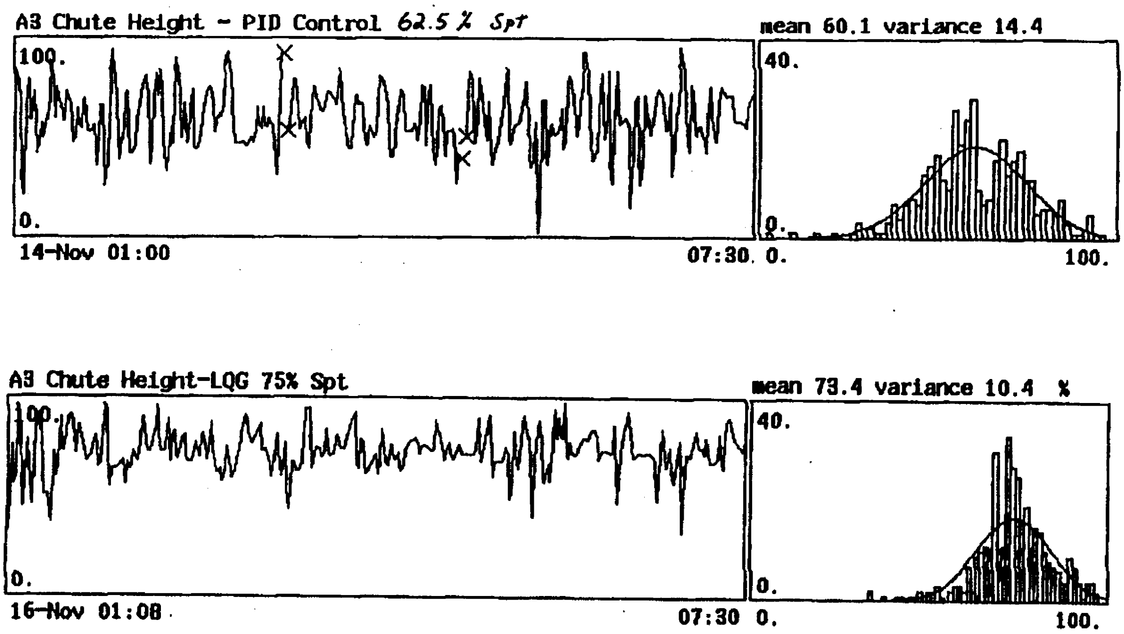

Figure 8.1: PID versus LQG chute height control - A3 Mill.

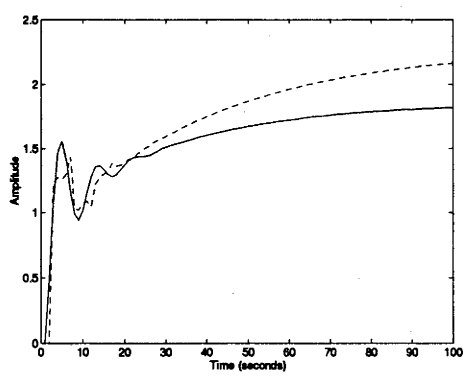

Figure 8.2: Step Response of Height Controllers using model-based LQG design (solid line) and direct LQG controller design (dashed line).

explicitly ignored. Consequently, analysis of process behaviour is usually hindered by the lack of any coupling assumptions. In particular, critical interactions resulting from closed loop behaviour, that is from process output to process input, are often overlooked.

Although the steady-state position of the flap has a significant influence on the steady-state torque, it is apparent from process modelling that the actuation of flap position is not a major influence on the dynamics of the torque. The mechanism by which the manipulation of the flap position exerts its influence on the process dynamics, is initially through chute height and then the height/speed loop. Assuming a uniform cane, a step increase in the flap position causes an approximate ramp increase in the chute height, which is normally reflected by an increase in the turbine speed due to the control action. The effect of the speed increase is twofold. Firstly, at increasingly higher speeds the mill rollers cannot maintain the torque due to increased slippage. Secondly, although the rise in speed suggests an increase in the volume of bagasse fed into the mill, this does not necessarily happen since the relative position of the flap is the overriding factor determining the available volume of cane. In most instances, the contribution to a decrease in torque due to slippage outweights any increase in torque associated with an increase in the volume of cane fed into the mill. These qualitative conclusions are based upon process observations during normal operation and the open loop step responses for the milling units considered in this dissertation. Although these conclusions are qualitative, they have motivated the torque regulation control strategy which has achieved some success in tightening torque deviations.

8.3.2 Torque Regulation

Traditional milling theory does not suggest that the torque is influenced by the speed of the mill rolls (Murry and Holt, 1967). The proposition to regulate the torque by manipulating the speed stems from recognising process variable interactions associated with the multi-variable nature of the crushing process.

Torque regulation can be achieved by manipulating the turbine speed. Torque regulation is weighted against a sometimes competing height regulation objective. The weighting is such that the height regulation objective gradually becomes more important as the chute height deviates further from set-point. The block diagram of the torque regulation strategy with a two-input one-output (2i1o) torque-height/speed controller was shown in Figure 5.3.

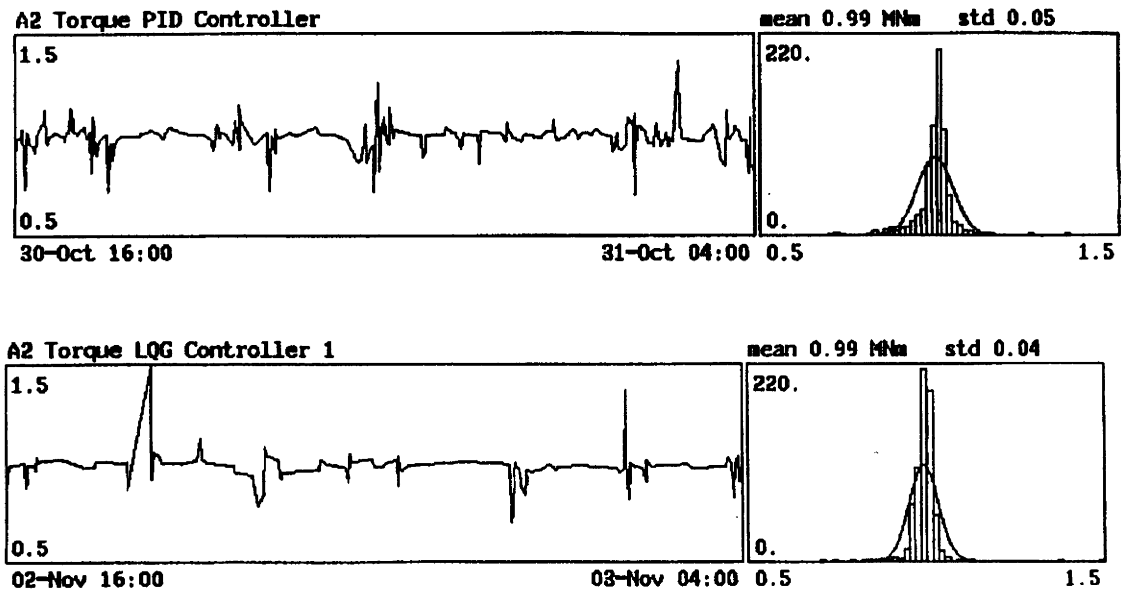

Figure 8.3: A2 mill torque regulation - PID versus LQG with C_0 during the 1993 crushing season. The torque set-point is 1.0 MNm.

The torque/flap position PID controller is maintained, since under steady-state conditions the relative flap position does have a considerable bearing on the steady-state torque.

In an attempt to achieve higher extraction through better torque regulation, 2i1o LQG torque controllers have been implemented on A2, A3, and A4 milling units at Victoria Mill during the 1991, 1993, and 1994 crushing seasons. The mill settings for each of the crushing units during these seasons is listed in Appendix E. The parameters of all the height and torque controllers referred to in this chapter are listed in Appendix F. For the record, the height and torque PID controller gains are tabled in Appendix G.

A2 Mill

The initial torque controller trials were conducted on the A2 milling unit during the 1991 crushing seasons. It was observed that with good feeding cane passing through A2 mill, the initial LQG torque controller, $C_0(\hat{P}_0)$, achieved significantly better torque regulation than the PID controller. However, with poor feeding cane, LQG control only marginally outperformed PID. Figure 8.3 illustrates that the overall performance of the LQG torque controller, $C_0(\hat{P}_0)$, is superior to that of PID control. Although the data in Figure 8.3 is from the 1993 crushing season, similar results were obtained during the 1991 crushing season (Partanen *et al*, 1994a). Statistical hypothesis testing (Mendenhall *et* *al*, 1986) confirms that the difference between standard deviations associated with torque signal data in Figure 8.3 is significant.

Remark 8.3.1 The frequency response magnitude plots for the multi-variable plant model, $\hat{P}_0$, used in the design of the initial LQG controller, $C_0(\hat{P}_0)$, are those of Figures 6.2 and Figure 6.3.

Given some encouragement from the results of Figure 8.3, and in order to obtain better control performance, the revised Zangscheme iterative design was trialled on A2 mill during the 1993 and 1994 crushing seasons. Recall, that the applicability of the Zangscheme iterative design to the sugar cane crushing process was justified in Section 5.3.4, on the grounds that readily available experimental and operational data can be used to direct future model-based control designs.

Using the initial controller, C_0, the following controllers resulted from the first two iterations of the revised Zangscheme iterative design :-

1. $C_1(\hat{P}_0)$, a frequency-weighted LQG controller from the application of one iteration of the direct variant of the Zangscheme. The performance of the controller, C_1, is given in Figure 8.4.

2. $C_2(\hat{P}_1)$, a standard non-frequency-weighted LQG controller, from the application of one iteration of the decoupled variant of the Zangscheme. The performance of the controller, C_2, is given in Figure 8.5. $\hat{P}_1$ was identified using the two-stage indirect method of closed loop identification, refer Section 3.4. The magnitude frequency and step response of the multi-variable plant model, $\hat{P}_1$, are those of Figure 6.4-6.7.

Figure 8.5 clearly shows that the controller, C_2, obtained after only two iterations of the Zangscheme has improved significantly the torque regulation. Also from Figure 8.5, note the corresponding tightness of the height regulation. The results depicted in Figures 8.3-8.5 were achieved during the 1993 crushing season.

Figure 8.6 compares the step responses of the LQG controllers, C_0, C_1, C_2, whilst Figure 8.7 displays the comparative frequency response plots. The low pass nature of the response to height and torque deviations is clearly evident in these controllers. The LQG controller, C_2, gained a significant performance enhancement through the extension of its bandwidth in response to the height and torque signals. C_2 has also benefited from the

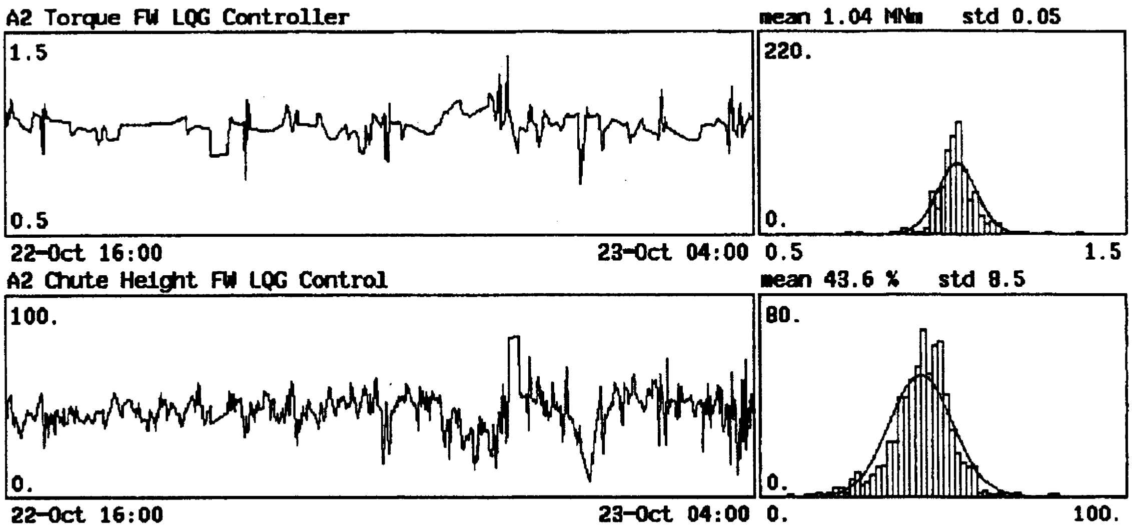

Figure 8.4: A2 mill LQG torque and chute height control performance with C_1 during the 1993 crushing season. The torque set-point is 1.0 MNm.

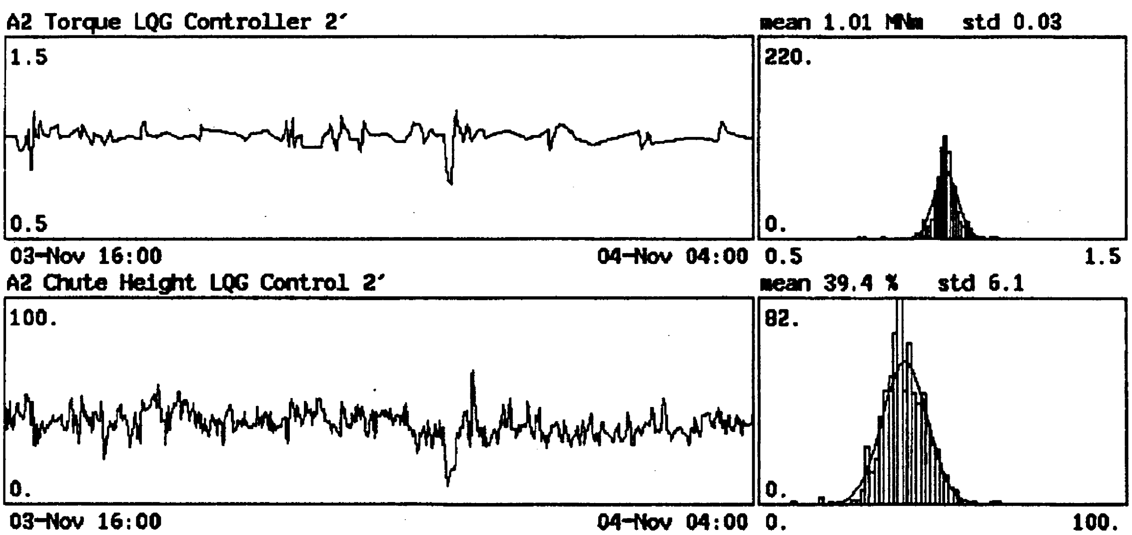

Figure 8.5: A2 mill LQG torque and chute height performance with C_2 during the 1993 crushing season. The torque set-point is 1.0 MNm and the chute height set-point is 40%.

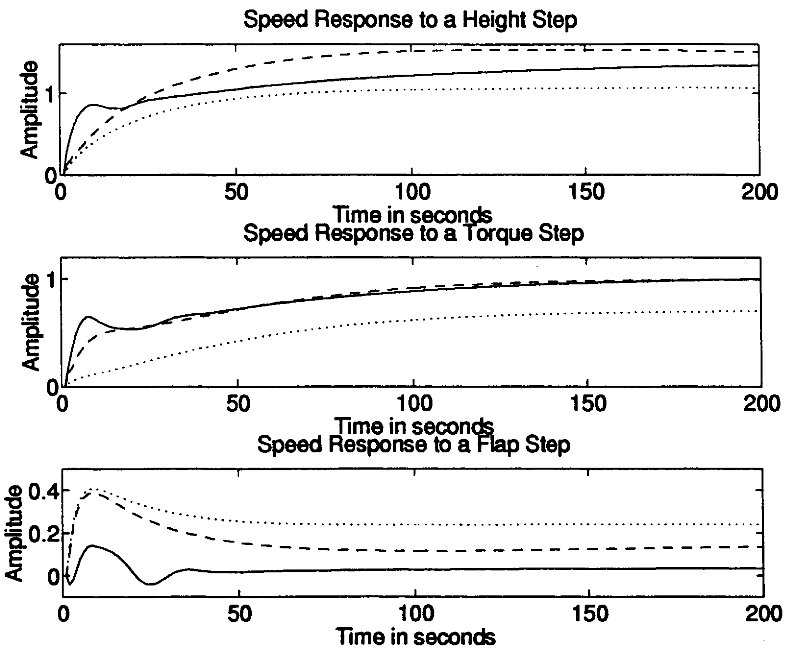

Figure 8.6: A comparison of A2 mill LQG controller step responses. C_0 dotted line, C_1 dashed line, C_2 solid line.

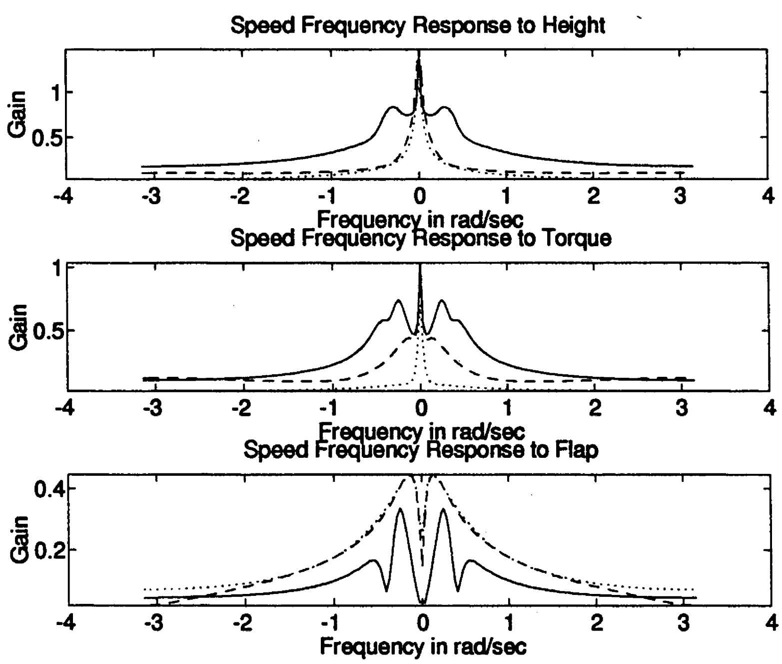

Figure 8.7: A comparison of A2 mill LQG controller frequency responses. C_0 dotted line, C_1 dashed line, C_2 solid line.

manner in which it treats the measurable disturbance imposed by the flap signals. *A priori* process knowledge suggests that variations in the flap position directly affect the chute height, however, the steady state flap position has little effect on the chute height due to compaction in the feed chute. Hence, the almost complete rejection of the steady state flap position after some initial control action in the control law of the final controller, refer Figure 8.6 and Figure 8.7.

Remark 8.3.2 The first iteration of the direct variant required that the frequency weightings were scaled with $\delta = 0.6$ to produce an open loop stable controller, $C_1(\hat{P}_0)$.

Remark 8.3.3 Data from the achieved closed loop system without any external excitation (except for the disturbance process) is used in the frequency weighting computations. That is, the frequency weightings are derived from disturbance driven data alone. A mechanism by which to capture additional plant model mismatch within the frequency weightings is to add excitation into the achieved closed loop system. However, this adds to the extent of deviations of the frequency weighting from unity, which in turn compromises the robust stability condition (4.15). Unfortunately, even by scaling, according to (7.15), those frequency weightings estimated from user chosen excitation driven closed loop data, the extent of the scaling necessary to produce a stable controller is such that the frequency weightings appear almost all-pass. That is, almost no frequency weighting is effected. This effect negates the original intention of using the excitation and disturbance driven frequency weightings for performance enhancement. Hence, in this application where stable controllers are required, input-output process data which is disturbance driven, as opposed to process data driven by both disturbance and excitation signals, is used to estimate the Zangscheme frequency weightings.

Remark 8.3.4 The second iteration of the direct variant resulted in a controller almost identical to the initial controller, C_0. Therefore, no significant performance enhancement could be expected. The application of the direct Zangscheme variant was suspended pending a new plant model.

Remark 8.3.5 Controller, $C_2(\hat{P}_1)$, is a standard non-frequency weighted LQG controller with user tuning available through the design parameters such as $R_c, R_o, \epsilon, \alpha, H^d$, recall Section 5.4. Application of the decoupled Zangscheme variant which includes the identification of plant model, $\hat{P}_1$, and the estimation of frequency weightings, F_1^h, F_1^t, F_2, produced unstable controllers for sensible choices of design parameters. The frequency weighting had to be scaled to such an extent that there was almost practically no weighting before the controller design delivered a stable controller. Although the requirement of an open-loop stable controller meant that controller, $C_2(\hat{P}_1)$, resulted from, for all practical purposes, a standard non-frequency-weighted LQG design, $C_2(\hat{P}_1)$ is still considered part of the Zangscheme iterative design since the identified plant model, $\hat{P}_1$, depends upon a frequency-weighted LQG controller, C_1. Furthermore, a standard non-frequency-weighted LQG controller design can be thought of as a special case of a frequency-weighted LQG controller design, with $F_1^h = 1,\ F_1^t = 1,\ F_2 = 1$.

Remark 8.3.6 During the third and four iterations of the revised Zangscheme it was observed that,

- the application of the direct variant did not produce a better performing controller than C_2.
- model adjustment through a single iteration of the decoupled Zangscheme variant delivered a new plant models, $\hat{P}_2 \approx \hat{P}_1$ and $\hat{P}_3 \approx \hat{P}_1$. With no perceived performance enhancement possible through the new models the revised Zangscheme was terminated.

This reinforces that the iterations of the Zangscheme iterative design are not meant to carried out indefinitely, and that in general most of the performance enhancement can be achieved in the first few iterations, recall Remarks 2.8.9 and 7.5.5.

Remark 8.3.7 During the control design, candidate controllers which did not pass the robust stability test (4.15) outlined in Lemma 4.2 were rejected.

The superior torque regulation achieved with controller, C_2, during the 1993 crushing season did not eventuate during the 1994 crushing season. Refer Figure 8.8. The use of operational data in a further two iterations of the revised Zangscheme produced controllers with similar torque regulation as C_2. Hence the controller, C_2, is considered as being close to the best available for the control design method selected. This also means that the controller, C_2, is close to local minimum of control performance. The possible *globality* of this local minimum is corroborated by whiteness test performed on the plant outputs. Statistical process control methods use output signal whiteness as a measure of

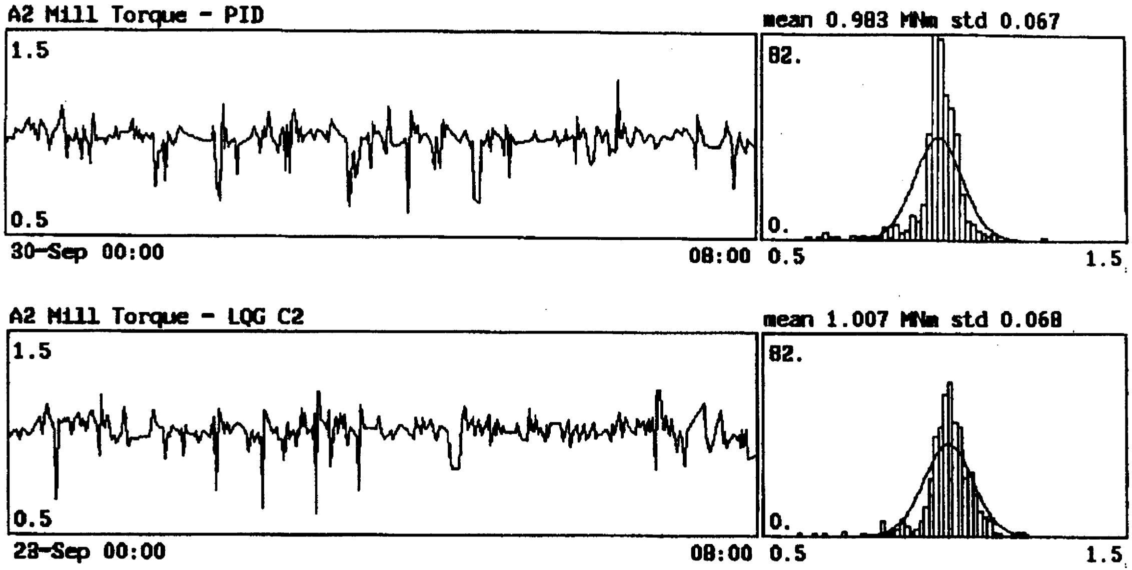

Figure 8.8: A2 mill LQG torque and chute height performance with C_2 during the 1994 crushing season. The torque set-point is 1.0 MNm.

achievement of minimum variance disturbance rejection (Wetherill and Brown, 1991). The change in performance of the controller, C_2, during the 1994 crushing seasons is mainly attributed to very poor feeding canes which dominated the cane supply during the 1994 crushing season. This is also reflected in the higher standard deviations of the torque histogram distributions for the 1994 crushing season compared with those for the 1993 season. As outlined in Section 8.2 the large percentage of poor feeding cane during the 1994 crushing season was probably due to a lack of rainfall and a significant increase in the tonnage of sugar cane harvested and supplied to the mill from marginal sugar cane growing districts. Poor feeding cane often resulted in process operation close to constraint values.

A3 Mill

The Zangscheme iterative design was also applied on A3 mill during the 1994 crushing season. The controller, C_2, from A2 mill was used as the initial controller, C_0, on $A3$ mill, as part of the Zangscheme iterative design, since the physics of the crushing process ought to be similar in both instances. The results were immediate, after one iteration tighter torque regulation was achieved with the new A3 mill torque controller, C_1. Refer

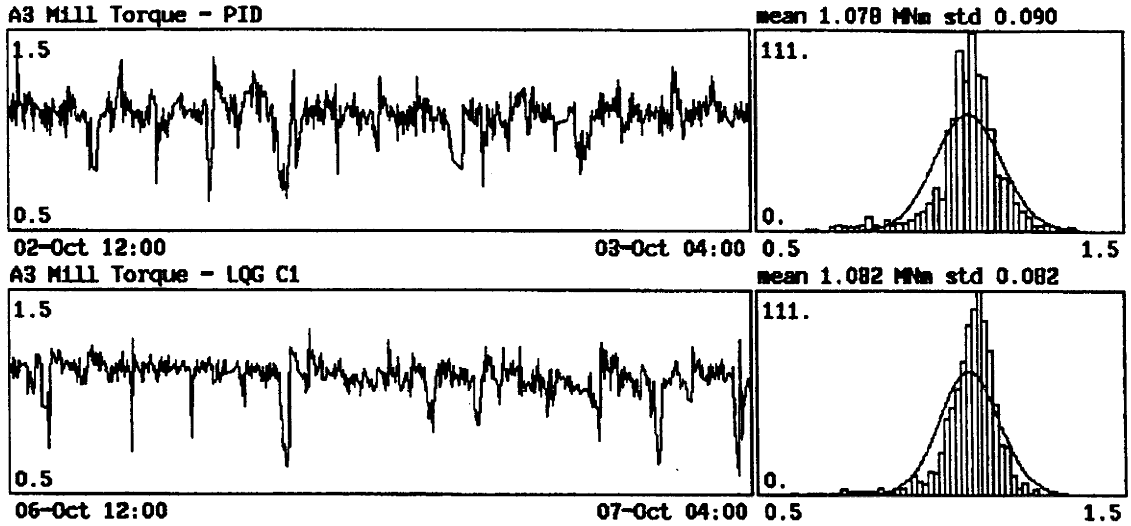

Figure 8.9: A3 mill LQG torque and chute height performance with C_1 during the 1994 crushing season. The torque set-point is 1.05 MNm.

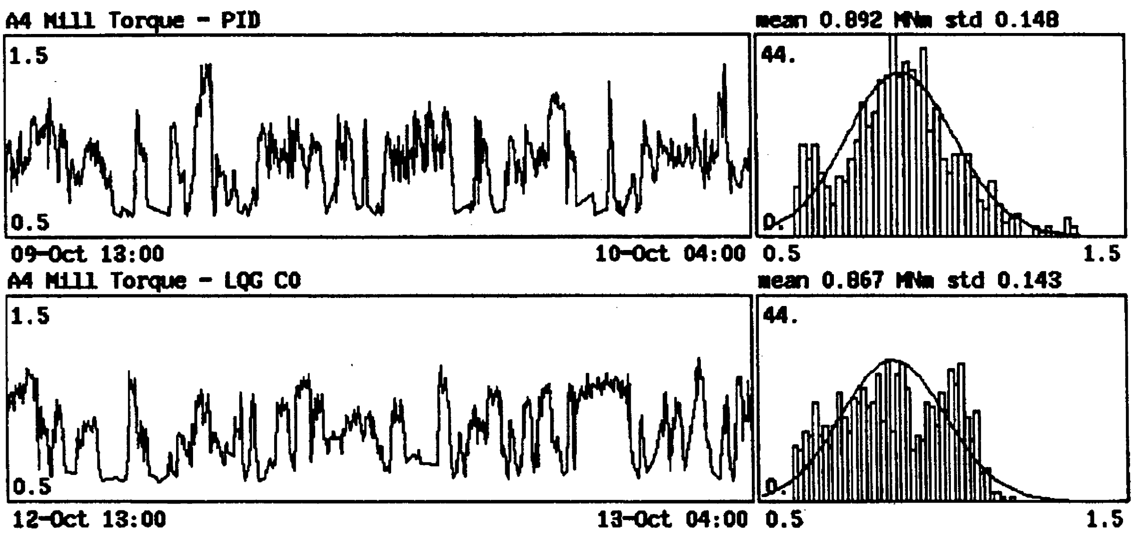

Figure 8.10: A4 mill LQG torque and chute height performance with C_2 during the 1994 crushing season. The torque set-point is 0.9 MNm.

Figure 8.9. Note, the reduction in the height of the histogram bins for the low and high end torques with LQG control. As in the case of A2 mill, subsequent iterations of the revised Zangscheme produced similar plant models and controllers, again suggesting with this controller type further improvements are not possible. This is the first LQG torque controller of many trialled since the 1991 crushing season (excluding the 1992 crushing season) which has clearly outperformed PID control on A3 mill. Previous attempts were hampered by the difficulty in validating identified process models. This difficulty was overcome by performing an identification experiment with an injected excitation signal which possessed a combined robust performance and robust stability agenda as described by Lemmata 4.1 and 4.2.

During the later weeks of the crushing season, for some canes, it was noted that the large juice flows around the circumference of the A3 mill pressure feeder rollers interferred with the feeding mechanism and consequently torques decreased. The action of the LQG torque controller caused surges in the juice flow, resulting in large torque fluctuations. This is indicative of nonlinear process behaviour. Under these circumstances, the operators often reverted back to PID control. The large juice flows over the pressure feeder rollers were peculiar to A3 mill.

In order for A3 mill to anticipate gross variations in the incoming cane, an LQG torque controller with feedforward information in the form of a delayed version of the A2 mill chute height signal was trialled. Since the characteristics of the bagasse change after each stage of crushing, this controller was no better at compensating for the gross variations in the feedstock than any of the other controllers trialled.

A4 Mill

The LQG torque controller, C_2, from A2 mill was also trialled as the initial controller, C_0, on A4 mill, during the 1994 crushing season. Refer Figure 8.10. LQG torque control produces isolated incidences of very good control which is seldom achieved with PID. Nevertheless, regardless of the controller design, the overall torque regulation is woeful[1].

The difficulty in controlling this crushing process prevented the identification of a suitable linear process model from closed loop input-output data. This suggests that modelling the A4 crushing process using linear time-invariant methods is inappropriate, since either

[1] As per Macquarie Dictionary Definition 3 - *of wretched quality.*

Mill	Control Method	Mean KW	Mean Steam Flow kg/hr	Saving in Steam Usage kg/hr
A2	PID	391	9400	
	LQG	356	8800	+640
A3	PID	356	10600	
	LQG	323	10300	+300

Table 8.1: Turbine Steam Usage - LQG vs. PID

time-varying and/or nonlinear effects dominate process behaviour. The results obtained on A4 mill highlight the need to consider nonlinear control techniques for application to the milling train, or a rethink of process design.

8.3.3 Energy Savings

Like most sugar mill operators, CSR Ltd factories generate their own steam and electricity by using bagasse as a fuel after it has passed through the crushing process. Excess electricity is exported and sold to the power supply company. Should the financial rewards in exporting electricity to the state power grid improve sufficiently, any energy savings resulting from improved control in the sugar mill could derive increased revenue through export power sales.

Although the primary objective of minimising torque deviations around a high set-point was not achieved with this project, a secondary benefit was realised through the use of LQG control. By using speed to control torque directly, the LQG controller is more energy efficient than the PID controller. Figure 8.11 and Figure 8.12 compare turbine power for A2 and A3 mill under LQG and PID control. Table compares the effect of LQG and PID control on turbine steam consumption for these two mills. Note, A2 and A3 mills are powered by different steam turbine types.

8.4 Technology Transfer

Although through the application of advanced control methods to the sugar cane crushing process, the financial rewards associated with higher extraction, have not yet been realised, successful implementation of the technology outlined in this paper has had a positive effect

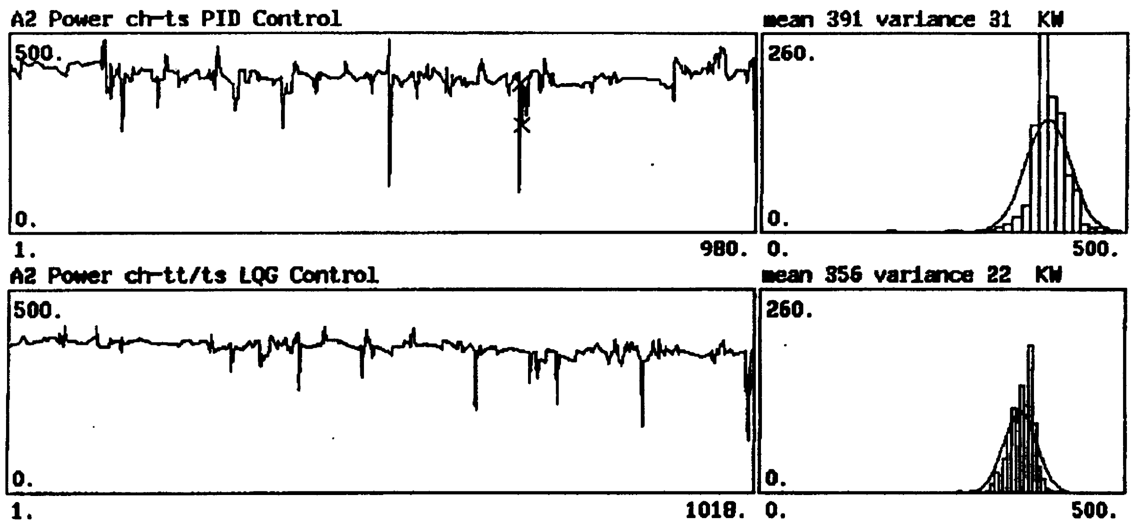

Figure 8.11: A2 mill turbine power under PID and LQG control.

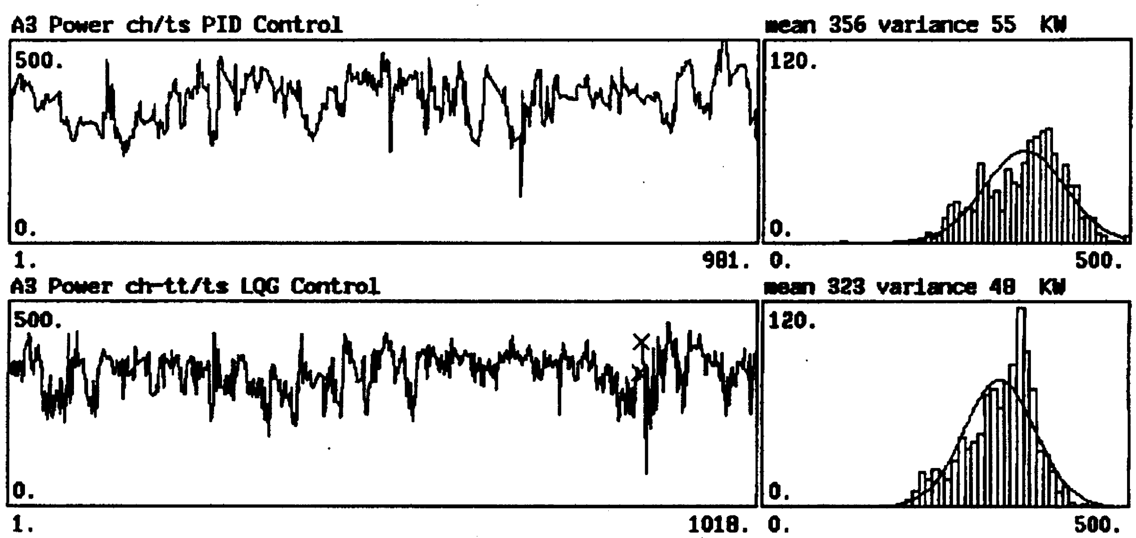

Figure 8.12: A3 mill turbine power under PID and LQG control.

on the implementation of related technology to other sugar milling process. For example,

- cross-correlation techniques have been used by Crisafulli *et al*, (1993) to estimate circulation rates in a continuous vacuum pan. Sugar crystals of a permissible tolerance are grown in the pan. Factory scale continuous vacuum pans are a relatively new process technology in the sugar industry. The circulation rate of the material inside the pan is critical to the operation of a continuous vacuum pan. Reliable estimates of the circulations rates have been useful in developing models of the process behaviour for this new process.

- Kalman filtering estimation techniques have been recently applied by Crisafulli *et al* (1994) to estimate the fibre to cane ratio. This is an important quantity for many aspects of sugar milling, as it is the only quantity which remains invariant throughout the milling train. A reliable estimate of the fibre to cane ratio is potentially very valuable.

Successful application of this technology in the sugar industry may promote similar experiences in other industries.

8.5 Chapter Conclusions

The application results demonstrate that the performance of the LQG torque controllers designed using linear time-invariant methods is sometimes limited by :-

- nonlinearities associated with the process behaviour.

- the interplay between the process constraints and the control action.

- gross variations in the dynamical characteristics of the process disturbances.

In spite of the fact that the LQG torque controllers were retro-fitted with *ad hoc* mechanisms to cope with some aspects of these limitations, as evidenced by the repeated survival of the controllers trialled over long time periods, significantly better process performance across the entire milling train was not forthcoming. A better approach is a controller design which directly incorporates these factors.

Although the application of controller refinement to the sugar cane crushing process has not fully delivered the anticipated extraction rewards, this application has provided some worthwhile theoretical and practical outcomes. For example,

- it was demonstrated that both direct and indirect closed loop identification methods can be successfully applied to identify models of a difficult-to-model industrial process for control purposes. A methodology for appropriately selecting identification design variables and reducing the effect of process specific vagaries was proposed.

- formulation of a disturbance rejection frequency weighted LQG control solution for the multi-variable sugar cane crushing process.

- testing of the Zangscheme iterative identification and control design on an industrial process. This application led to the development of a revised version of the Zangscheme which includes infrequent model identification and cautious controller enhancement.

- a better understanding of the multi-variable nature of the crushing process under closed loop conditions was obtained.

For CSR Ltd, this project highlights what can and cannot be achieved in terms of crushing process performance using linear time-invariant control design methods. In addition, this application of model-based control design has inspired and motivated application of related signal processing techniques to other processes in a raw sugar factory.

This thesis highlights that Australian raw sugar factories are well placed in terms of the degree of automation necessary for application of model-based multi-variable control design methods. Furthermore, the successful application of state-of-the-art model-based multi-variable design methods to an industrial process indicates that this sort of work can be performed by Australians trained in Australia.

Chapter 9

Conclusions and Further Research

9.1 Summary of Contributions

This thesis has covered a number of different topics in the area of System Identification and Robust Control. Research questions investigated centre around the Zangscheme iterative identification and control design scheme with the intention of using this methodology to refine the existing feedback controllers to regulate better individual sugar cane crushing units in a multi-stage milling train. Closed loop regulation of these individual units in response to variations in the physical attributes of the incoming sugar cane plays an important role in determining the extraction performance of a milling train. Therefore, the milling train is an important element in determining the efficiency and profitability of a raw sugar factory.

Like many industrial processes, the sugar cane crushing process can, at best, be crudely approximated by linear time-invariant models. Nevertheless, iterative designs using available System Identification and Robust Control techniques provide a relatively immediate solution for developing controllers which can achieve high performance on the process which is being approximated.

Given that, today, as a result of ongoing factory automation, many western world factories, raw sugar factories included, continually log operational data, one relevant research endeavour is to understand better how readily available operational data can be used to improve process closed loop performance. In the context of iterative identification and control design methods, operational data plays an important role in directing the model adjustment and controller design steps.

The major contributions contained in this thesis are summarised below.

- **Closed Loop Identification Criterion [Section 3.3]:** The criterion associated with applying directly prediction error methods to the identification of plant input-output transfer function models from closed loop input-output data was derived. This criterion highlights the importance of performing a closed loop identification experiment with a suitably chosen excitation signal injected at the plant input.

- **Selection of Closed Loop Identification Design Variables [Chapter 6]:** The closed loop identification criterion derived in Section 3.3 is fundamental to understanding how the selection of various design variables impinges upon the identification outcome. For the sugar cane crushing process, it was shown that *a priori* process knowledge can be explicitly incorporated into a design methodology for the selection of identification design variables. The conformance of identified models to *a priori* knowledge is the determining factor in the final acceptance of any candidate model for control design.

- **Zangscheme Variants [Chapter 7]:** The original Zangscheme is an iterative identification and control design in which one iteration consists of a model adjustment step followed by a controller enhancement step. Two variants of the original Zangscheme were proposed. In the decoupled variant, the dependence of the current iteration's controller enhancement step upon the plant model from the previous iteration is removed. Hence, the closed loop input-output signals used to estimate the frequency weighting which weight the LQG control design criterion are now better aligned with the other closed loop input-output signals that appear in the control criterion. Simulation evidence shows that the decoupled variant results in better achieved closed loop performance in fewer iterations than the original Zangscheme. With the direct Zangscheme variant, an initial plant model is the only plant model used. The controllers are updated using newly estimated frequency weightings, hence, avoiding the need for an identification experiment.

- **Cautious Controller Enhancement [Chapter 7]:** By scaling the effect of the frequency weightings, it was shown that cautious controller enhancement can be introduced into the Zangscheme.

- **Revised Zangscheme [Chapter 7]:** The revised Zangscheme consists of a composite iterative design using a combination of the decoupled and direct Zangscheme variants with cautious controller enhancement through scalable frequency weightings.

- **"Innovations" signals in Frequency Weighted Controller Design [Chapter 7]:** With the original Zangscheme iterative design, full-scale frequency weightings estimated from closed loop input-output data are used to weight an LQG controller design. One way of gauging the suitability of this design modification to LQG control design is to examine the whiteness of the so-called *predicted difference* signal. The predicted difference signal records the additive error between the measured achieved closed loop output and the output of the Kalman predictor part of the LQG controller. Ideally, the predicted difference signal should be white. In general, with restricted complexity controller design using standard LQG methods, this predicted difference signal will not be white. With frequency weighted controllers of the Zangscheme, it was shown that the effect of frequency weightings is to whiten the achieved closed loop's predicted difference signal. Although the full implications of this result are far from clear, it provides an informal connection between iterative controller design using closed loop data and restricted complexity controllers.

- **Formulation of LQG Control Objectives for the Sugar Cane Crushing Process [Chapter 5]:** The justification for formulating an LQG control solution of the sugar cane process was based on a number of process specific practical considerations. Two control strategies were formulated for the sugar cane crushing process. Initially, it was perceived that better extraction performance of an individual crushing mill could be achieved using a control strategy which minimised height deviations during normal process operation at a height set-point significantly higher than was possible with existing PID control. Bagasse compaction in a vertical chute is known to increase with chute height. Traditional milling theory reveals that high bagasse compaction translates to better feeding and consequently higher torques can be exerted by the milling rollers on the sugar cane fibre with a resultant improvement in extraction. Therefore, LQG height controllers were designed and trialled. Although LQG height controllers were proved capable of minimising height deviations about a high set-point, the average turbine torque level did not rise as expected, it in fact decreased, which meant that mill extraction suffered. Traditional milling theory does not take into account the multi-variable nature of the closed loop interactions. When this is done, an alternative control strategy to minimise turbine torque deviations about a set-point was adopted. This torque control strategy, as opposed to the previously trialled height control, relied upon speed to control a weighted torque and height objective which also included a control penalty. Height control still needed to be included in this objective since the full and empty limits of the chute are, very much, active constraints in the operation of the crushing process.

- **Application of the Revised Zangscheme to the Sugar Cane Crushing Mill [Chapter 8]:** Initially, the newly adopted torque control strategy realised similar closed loop performance to that achieved under the existing PID control. Lack of performance improvement necessitated the application of controller refinement in order to acquire controllers which would significantly improve process closed loop performance. On A2 mill, the second crushing unit in a four-stage milling train, the revised Zangscheme was successful in delivering LQG torque controllers which significantly tightened torque deviations during normal process operation at a high torque set-point. Unfortunately, this performance could not be maintained for extreme variations in the physical properties of the incoming sugar cane. Application of linear time-invariant controller refinement methods, such as the revised Zangscheme, to the latter milling units, A3 and A4, were hampered not only by gross feedstock variations, but also non-linearities associated with process behaviour, and the interplay between the process constraints and the control action.

9.2 Further Research

Throughout this thesis, many issues have been raised which are potential topics for further research work. The future research has been subdivided in those which concern System Identification and Robust Control and those which serve to obtain a better understanding and hopefully better control of the sugar cane crushing process.

9.2.1 System Identification and Control Design

Justified from an applications perspective, this thesis has identified the following theoretical research avenues open for further investigation.

- **Control-relevant Identification for LQG Disturbance Rejection:** For the sugar cane crushing process, the disturbance rejection controller design was performed with disturbance models which conformed with qualitative *a priori* information regarding the effect of cane variety disturbances on the output process variables. Hence, the *a priori* output disturbance models are only approximate, in the sense that these models are guesses of the true disturbance process. For most industrial processes, the use of approximate disturbances is likely to be the norm. With a fixed and approximate disturbance model, the performance degradation criterion associated with LQG disturbance rejection does not induce a related identification criterion, in contrast to the situation for exact disturbance knowledge, recall Lemma 4.1. Conceivably the performance degradation criterion could be minimised approximately using an optimisation procedure, as was considered in Remark 4.2.9. Further research work is required to check the suitability of this approach, before any serious software development for the algorithm could be attempted.

- **Direct versus Indirect Closed Loop Identification:** In the author's opinion, it is still unclear as to which closed loop identification approach, direct or indirect, is better suited for the purposes of identifying models for control design from closed loop input-output data obtained from systems which are approximately linear time-invariant and for which an exact disturbance description is not available. Unlike the indirect methods, direct prediction error closed loop identification will result in the identification of biased estimates of the plant, P, if the disturbance model is incorrect. Under which circumstances will this bias be beneficial for control design is a topic for further research, and is closely related to the previously outlined further research subject of control-relevant identification for LQG disturbance rejection control.

- **Frequency Weighted Controller Design:** Although, the whitening effect of frequency weightings upon the achieved closed loop Kalman Predictor innovations process was presented in this thesis, the full implication of this result with respect to analysing the optimality of a given control design for an unknown plant and disturbance pair requires further investigation.

9.2.2 Sugar Cane Crushing Process

If further control-related research is to continue for the sugar cane crushing, the following approach to modelling and control ought to be examined.

- **Direct iterative design** For A2 mill, where the non-linear behaviour is minimal, it is conceivably possible to use a multi-variable version of the direct controller design of Hjalmarsson *et al* (1995, 1994b, 1994c) to adjust the controller parameters when a gross change in the incoming cane occurs. This approach requires reliable change detection.

- **Nonlinear Predictive Control with Constraint Handling** An alternative approach which could be used on all the milling units is nonlinear predictive control with constraint handling in conjunction with feedforward control for rejection of the process disturbances. The appropriate feedforward signals need to be estimated. This approach could also be used to realise an adaptive solution in which the controller parameters are being continuously adjusted.

- **Nonlinear Modelling** In order to proceed with nonlinear control design, a nonlinear mathematical model based on a thorough understanding of the physics of the process is required. The formulation and validation of a nonlinear model will require considerable effort. Alternatively, nonlinear System Identification methods, (for a survey see Haber and Unbehauen (1990)), could possibly be applied to identify nonlinear polynomial models from process input-output data. To the author, at least, it is unclear whether such nonlinear System Identification techniques could be readily applied with closed loop input-output data.

9.3 Conclusion

This thesis has provided an engineering solution to the gradual refinement of existing controllers for performance enhancement of a sugar cane crushing process. A broad range of theoretical and practical problems associated with System Identification and Robust

Control have been treated. Both these design techiques have been considered in the context of enhancing closed loop performance through iterative identification and control design. The emphasis in this treatment has been the use of readily available process input-output data, either operational or experimental, during the model adjustment and control enhancement steps of the Zangscheme iterative design.

Despite successfully implementing multi-variable model-based control strategies on the sugar cane crushing process, the anticipated extraction benefit has not been fully realised. To attain the considerable financial rewards associated with higher extraction, the controller solution needs to accommodate specifically the factors which limit the current design. Application of such design techniques to industrial processes is in its infancy. As such the theory-practice gap is large. Consequently, for this difficult-to-control industrial process, further evolution of the control solution will necessarily involve lengthy research and development time, before the pot of sugar at the end of the milling train can be pocketed.

9.4 Coda

It should be noted that model-based multi-variable control work on the sugar cane crushing process was started in 1989. The evolution of a engineering solution to the crushing process has spanned the five crushing seasons, 1989-91, 1993-94. In his critique on process control for the chemical industry, Foss (1973) noted,

> *the theory of chemical process control has some rugged terrain to traverse before it meets the needs of those who apply.*

Although this statement was a generalisation of the state of chemical process control over twenty years ago, today following five years of controller trials for the difficult-to-control sugar cane crushing process, it is still just as pertinent.

Appendix A

Closed Loop Identification Multi-variable Formula

The frequency domain closed loop identification formula associated with the direct prediction error method is stated only for the single-input, single-output case in Theorem 3.1, page 14. Here the formula is extended to the multi-variable case. Refer to Figure 2.1 to define the signals, where now the signals are appropriately sized vectors and P and C are matrix transfer functions.

Elementary calculations yield

$$u(k) = (I + C(z)P(z))^{-1} r(k) - (I + C(z)P(z))^{-1} C(z)v(k).$$

Consider the prediction error, $\epsilon^j(k)$, of the jth element of the output, $y^j(k)$, and denote the noise model for the jth element of the disturbance, $v^j(k)$, by $\hat{H}^j(z)$, then,

$$\epsilon^j(k) = \hat{H}^{j,-1}(z) \left[\left(P(z) - \hat{P}(z,\theta) \right)^j u(k) + v^j(k) \right], \tag{A.1}$$

where $(\cdot)^j$ means the jth row. Substituting for $u(k)$ in terms of the exogenous signals yields,

$$\epsilon^j(k) = \hat{H}^{j,-1} \left[\left(P - \hat{P} \right)^j (I + CP)^{-1} r(k) - \left(P - \hat{P} \right)^j (I + CP)^{-1} Cv(k) + v^j(k) \right]. \tag{A.2}$$

Applying the identity

$$(I + CP)^{-1}C = C(I + PC)^{-1}$$

and writing

$$
\begin{aligned}
v^j(k) &= (I)^j (I + PC)(I + PC)^{-1} v(k) \\
&= (I + PC)^j (I + PC)^{-1} v(k)
\end{aligned}
$$

permits us to aggregate the $v(k)$ terms in (A.2)

$$
\epsilon^j(k) = \hat{H}^{j,-1} \left[\left(P - \hat{P}\right)^j (I + CP)^{-1} r(k) - \left(I + \hat{P}C\right)^j (I + PC)^{-1} v(k). \right] \tag{A.3}
$$

This is the multi-variable version of (3.8).

Appendix B

Proof of Lemma 4.3

Substituting for coprime factors, N_i, D_i, in (4.28) gives

$$\begin{aligned}
\hat{P}_{i+1} &= \frac{\hat{P}_i + \hat{R}Y}{1 - \hat{R}X}, && \text{(B.1)}\\
&= \hat{P}_i + \frac{\hat{P}_i + \hat{R}Y}{1 - \hat{R}X} - \hat{P}_i,\\
&= \hat{P}_i + \frac{\hat{P}_i + \hat{R}Y - \hat{P}_i + R\hat{P}_i X}{1 - \hat{R}X},\\
&= \hat{P}_i + \frac{\hat{R}(Y + \hat{P}_i X)}{1 - \hat{R}X}. && \text{(B.2)}
\end{aligned}$$

Substituting for coprime factors, X, Y, in the numerator of (B.2) as per (4.30) yields,

$$\hat{P}_{i+1} = \hat{P}_i + \frac{\hat{R}}{1 - \hat{R}X}. \tag{B.3}$$

Now,

$$\begin{aligned}
\hat{R} &= (\hat{P}_{i+1} - \hat{P}_i)(1 - \hat{R}X),\\
&= (\hat{P}_{i+1} - \hat{P}_i) - (\hat{P}_{i+1} - \hat{P}_i)X\hat{R}.
\end{aligned}$$

Bring all terms in $\hat{R}$ to the left hand side, and substituting for X as per (4.30 gives,

$$\begin{aligned}
\hat{R}\left[1 + (\hat{P}_{i+1} - \hat{P}_i)\frac{C}{1 + C\hat{P}_i}\right] &= (\hat{P}_{i+1} - \hat{P}_i),\\
\hat{R}(1 + C\hat{P}_i + C\hat{P}_{i+1} - C\hat{P}_i)\frac{C}{1 + C\hat{P}_i} &= (\hat{P}_{i+1} - \hat{P}_i).
\end{aligned}$$

Hence, proving the result,

$$\hat{R} = \frac{(\hat{P}_{i+1} - \hat{P}_i)(1 + C\hat{P}_{i+1})}{(1 + C\hat{P}_{i+1})} \tag{4.31}$$

Proof of Theorem 4.3

Substituting the complementary sensitivity function, $\hat{T} = \frac{C\hat{P}_i}{1+C\hat{P}_i}$, dual Youla-parameter equation, (4.31), and signal expressions, (3.35) and (3.36), into the filtered output error equation, (4.33), gives,

$$\begin{aligned}
\xi(k) &= \frac{1}{1+C\hat{P}_i}\left[\left(\frac{P-\hat{P}_i}{1+CP} - \frac{(\hat{P}_{i+1}-\hat{P}_i)(1+C\hat{P}_i)}{(1+C\hat{P}_{i+1})(1+C\hat{P}_i)}\right) r(k) + \frac{(1+C\hat{P}_i)H}{(1+CP)}e(k)\right], \\
&= \frac{1}{1+C\hat{P}_i}\left(\frac{P-\hat{P}_i}{1+CP} - \frac{(\hat{P}_{i+1}-\hat{P}_i)}{(1+C\hat{P}_{i+1})}\right) r(k) + \frac{H}{(1+CP)}e(k), \\
&= \frac{(P-\hat{P}_{i+1})(1+C\hat{P}_i)}{(1+C\hat{P}_i)(1+CP)(1+C\hat{P}_{i+1})} r(k) + \frac{H}{(1+CP)}e(k).
\end{aligned} \tag{B.4}$$

Hence, proving the result

$$\xi(k) = \frac{P-\hat{P}_{i+1}}{(1+CP)(1+C\hat{P}_{i+1})} r(k) + \frac{H}{1+CP}e(k). \tag{4.33}$$

Appendix C

Frequency Weighted LQG Controller Design for a Sugar Cane Crushing Mill

This appendix describes how a 2i2o model description can be used to obtain an implementable frequency weighted LQG controller. Zang *et al* (1990) have recast the non-standard frequency weighted LQ minimisation as standard LQ minimisation by applying frequency transformations. The frequency transformations can be used to construct a new transformed state space system from the initial 2i2o model description (5.7). This gargantuan system is composed of many state space subsystems. The gargantuan state space system is then used to construct a LQG controller $\bar{C}$. The frequency weightings embedded in this controller must be removed to give a frequency weighted LQG controller C ready for implementation.

The frequency transformation of the initial 2i2o model of (5.7) gives,

$$\begin{aligned}\begin{pmatrix} F_1^h(z)h_k^c \\ F_1^t(z)t_k^c \end{pmatrix} &= \begin{pmatrix} F_1^h(z)\hat{P}_{hs}(z)F_2^{-1}(z) & F_1^h(z)\hat{P}_{hf}(z) \\ F_1^t(z)\hat{P}_{ts}F_2^{-1}(z) & F_1^t(z)\hat{P}_{tf}(z) \end{pmatrix} \begin{pmatrix} F_2(z)s_k^c \\ f_k \end{pmatrix} \\ &+ \begin{pmatrix} F_1^h(z)V_h(z) \\ F_1^t(z)V_k(z) \end{pmatrix} e_k. \end{aligned} \tag{C.1}$$

By making the appropriate assignments, the following frequency transformed 2i2o model can be written,

$$\begin{pmatrix} \bar{h}_k \\ \bar{t}_k \end{pmatrix} = \begin{pmatrix} \hat{\bar{P}}_{hs}(z) & \hat{\bar{P}}_{hf}(z) \\ \hat{\bar{P}}_{ts}(z) & \hat{\bar{P}}_{tf}(z) \end{pmatrix} \begin{pmatrix} \bar{s}_k \\ f_k \end{pmatrix} + \begin{pmatrix} \hat{\bar{V}}^h(z) \\ \hat{\bar{V}}^t(z) \end{pmatrix} e_k. \tag{C.2}$$

This transfer function description can be written in a standard form involving distinct, yet coupled, controllable and observable state subspaces. That is, a gargantuan state space system of the form,

$$\begin{aligned}
\bar{x}^m_{k+1} &= F^m\bar{x}^m_k + G^m\bar{u}^m_k + L^m w^m_k, && \text{(C.3)}\\
&= \begin{pmatrix} F & F^a \\ 0 & F^d \end{pmatrix}\begin{pmatrix} \bar{x} \\ \bar{x}^d \end{pmatrix}_k + \begin{pmatrix} G \\ 0 \end{pmatrix}\begin{pmatrix} \bar{s}_k \\ f_k \end{pmatrix} + \begin{pmatrix} 0 \\ L \end{pmatrix} w^m_k, && \text{(C.4)}\\
\begin{pmatrix} \bar{h}_k \\ \bar{t}_k \end{pmatrix} &= H^m\bar{x}^m_k + q_k, && \text{(C.5)}\\
&= \begin{pmatrix} H & H^d \end{pmatrix}\begin{pmatrix} \bar{x} \\ \bar{x}^d \end{pmatrix}_k + q_k, && \text{(C.6)}
\end{aligned}$$

where w^m_k and q_k are white noise processes.

The state space model for $\tilde{s}_k = F_2^{-1}\bar{s}_k$ is

$$\begin{aligned}
x^h_{k+1} &= F^h x^h_k + G^h\bar{s}_k, && \text{(C.7)}\\
\tilde{s}_k &= H^h x^h_k + J^h\bar{s}_k. && \text{(C.8)}
\end{aligned}$$

The state space model for the frequency transformed disturbance signals $\bar{e}^h_k = F^h_1 e^h_k$ and $\bar{e}^t_k = F^t_1 e^t_k$ is,

$$\begin{aligned}
\begin{pmatrix} x^{dh}_{k+1} \\ x^{dt}_{k+1} \end{pmatrix} &= \begin{pmatrix} F^{fh} & 0 \\ 0 & F^{dt} \end{pmatrix}\begin{pmatrix} x^{dh}_k \\ x^{dt}_k \end{pmatrix} + \begin{pmatrix} G^{dh} & 0 \\ 0 & G^{dt} \end{pmatrix}\begin{pmatrix} e^h_k \\ e^t_k \end{pmatrix}, && \text{(C.9)}\\
\begin{pmatrix} \bar{v}^h_k \\ \bar{v}^t_k \end{pmatrix} &= \begin{pmatrix} H^{dh} & 0 \\ 0 & H^{dt} \end{pmatrix}\begin{pmatrix} x^{dh}_k \\ x^{dt}_k \end{pmatrix} + \begin{pmatrix} J^{dh} & 0 \\ 0 & J^{dt} \end{pmatrix}\begin{pmatrix} e^h_k \\ e^t_k \end{pmatrix}. && \text{(C.10)}
\end{aligned}$$

The state space model for the disturbance process $\bar{v}^h_k = \hat{V}^h\bar{e}^h_k$ and $\bar{v}^t_k = \hat{V}^t\bar{e}^t_k$ is,

$$\begin{aligned}
x^v_{k+1} &= F^v x^v_k + G^v\begin{pmatrix} \bar{e}^h_k \\ \bar{e}^t_k \end{pmatrix}, && \text{(C.11)}\\
\bar{v}^h_k &= H^{vh} x^v_k, && \text{(C.12)}\\
\bar{v}^t_k &= H^{vt} x^v_k. && \text{(C.13)}
\end{aligned}$$

The characteristics of the disturbance processes for the height and torque models are known, *a priori*, to contain steps and ramps, recall Section 6.3.1. A combined height and torque disturbance model was composed based on this *a priori* knowledge, with the same poles for $\hat{V}^h$ and $\hat{V}^t$.

The state space model for $\tilde{h}_k = \hat{P}_{hs}\tilde{s}_k + \hat{P}_{hf}f_k$ is,

$$x^1_{k+1} = F^1 x^1_k + (\,G^{1s} \quad G^{1f}\,)\begin{pmatrix}\tilde{s}_k \\ f_k\end{pmatrix}, \tag{C.14}$$

$$\tilde{h}_k = H^1 x^1_k. \tag{C.15}$$

The state space model for $\tilde{t}_k = \hat{P}_{ts}\tilde{s}_k + \hat{P}_{tf}f_k$ is,

$$x^2_{k+1} = F^2 x^2_k + (\,G^{2s} \quad G^{2f}\,)\begin{pmatrix}\tilde{s}_k \\ f_k\end{pmatrix}, \tag{C.16}$$

$$\tilde{t}_k = H^2 x^2_k. \tag{C.17}$$

The state space model for $\bar{h}_k = F^h_1(\tilde{h}_k + \bar{v}^h_k)$ is,

$$x^r_{k+1} = F^r x^r_k + G^r(\tilde{h}_k + \bar{v}^h_k), \tag{C.18}$$

$$\bar{h}_k = H^r x^r_k + J^r(\tilde{h}_k + \bar{v}^h_k). \tag{C.19}$$

The state space model for $\bar{t}_k = F^t_1(\tilde{t}_k + \bar{v}^t_k)$ is,

$$x^s_{k+1} = F^s x^s_k + G^s(\tilde{h}_k + \bar{v}^h_k), \tag{C.20}$$

$$\bar{t}_k = H^s x^s_k + J^s(\tilde{h}_k + \bar{v}^t_k). \tag{C.21}$$

Now, define the gargantuan state space vector x^m_k as,

$$x^m_k = [\,x^h \quad x^1 \quad x^2 \quad x^r \quad x^s \quad x^v \quad x^{dh} \quad x^{dt}\,]^T_k \tag{C.22}$$

The gargantuan state space system defined by state and observation equations (C.3) and

(C.5) can now be formed with,

$$F^m = \begin{pmatrix} F^h & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ G^{1s}H^h & F^1 & 0 & 0 & 0 & 0 & 0 & 0 \\ G^{2s}H^h & 0 & F^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & G^r H^1 & 0 & F^r & 0 & G^r H^{vh} & 0 & 0 \\ 0 & 0 & G^s H^2 & 0 & F^s & G^s H^{vt} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & F^v & G^v H^{dh} & G^v H^{dt} \\ 0 & 0 & 0 & 0 & 0 & 0 & F^{dh} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & F^{dt} \end{pmatrix}, \tag{C.23}$$

$$G^m = \begin{pmatrix} G^h & 0 \\ G^{1s}J^h & G^{1f} \\ G^{2s}J^h & G^{2f} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}, \quad L^m = \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ G^v J^{dh} & G^v J^{dt} \\ G^{dh} & 0 \\ 0 & G^{dt} \end{pmatrix}, \tag{C.24}$$

$$H^m = \begin{pmatrix} 0 & J^r H^{1s} & 0 & H^r & 0 & J^r H^{vh} & 0 & 0 \\ 0 & 0 & J^s H^{2s} & 0 & H^s & J^s H^{vt} & 0 & 0 \end{pmatrix}, \tag{C.25}$$

$$w_k^m = \begin{pmatrix} e_k^h \\ e_k^t \end{pmatrix}. \tag{C.26}$$

With the above gargantuan state space system, the state and control weighting matrices, Q_c, R_c for the LQ minimisation, and the process and measurement noise covariance matrices, Q_0, R_0 for the Kalman predictor were chosen as per Section 5.4.3.

The solution to the LQ regulator problem involves recognising that the gargantuan state space is made up of the controllable and observable subspaces as described in (C.4) and (C.6). The solution decomposes to calculating the state covariance matrices P^{11}, P^{12} to yield the control gains K^{11}, K^{13} in the control law (Bitmead *et al*, 1990),

$$\begin{aligned} \bar{s}_k &= -(G^T P_j^{11} G + R_c)^{-1} \left(G^T P_j^{11} F \quad G^T P_j^{12} F^d + G^T P_j^{11} F^a \right), & \text{(C.27)} \\ &= -\left(K^{11} \quad K^{13} \right) \begin{pmatrix} \bar{x}_k \\ \bar{x}_d \end{pmatrix}. & \text{(C.28)} \end{aligned}$$

P_j^{11} satisfies a Riccati Difference Equation (RDE),

$$P_{j+1}^{11} = F^T P_j^{11} F - F^T P_j^{11} G(G^T P_j^{11} G + R_c)^{-1} G P_j^{11} F + H^T Q_c H, \tag{C.29}$$

and P_j^{12} satisfies a Lyapunov equation,

$$P_{j+1}^{12} = (F - GK^{11})^T P_j^{12} F^d + (F - GK^{11})^T P_j^{11} F^a + H^T Q_c H^d. \tag{C.30}$$

The solution to the Kalman Predictor problem is standard, refer Bitmead *et al*, (1990). The resulting LQG controller, $\bar{C}$, is of the form,

$$\bar{s}_k = \begin{pmatrix} \bar{C}_{sh} & \bar{C}_{st} \end{pmatrix} \begin{pmatrix} \bar{h}_k \\ \bar{t}_k \end{pmatrix} + \bar{C}_{sf} f_k. \tag{C.31}$$

The frequency weightings embedded in this solution must be removed to realise the frequency weighted control law for s_k. The embedded frequency weightings are evident when (C.31) is written as,

$$F_2 s_k^c = \begin{pmatrix} \bar{C}_{sh} & \bar{C}_{st} \end{pmatrix} \begin{pmatrix} F_1^h h_k^c \\ F_1^t t_k^c \end{pmatrix} + \bar{C}_{sf} f_k. \tag{C.32}$$

$$s_k^c = \begin{pmatrix} \bar{C}_{sh} F_2^{-1} F_1^h & \bar{C}_{st} F_2^{-1} F_1^t \end{pmatrix} \begin{pmatrix} h_k^c \\ t_k^c \end{pmatrix} + \bar{C}_{sf} F_2^{-1} f_k. \tag{C.33}$$

The state space model for $h_k' = F_h^1 h_k^c$ is,

$$x_{k+1}^p = F^r x_k^p + G^r h_k^c, \tag{C.34}$$

$$h_k' = H^r x_k^p + J^r h_k^c. \tag{C.35}$$

The state space model for $t_k' = F_t^1 t_k^c$ is,

$$x_{k+1}^q = F^s x_k^q + G^s t_k^c, \tag{C.36}$$

$$t_k' = H^s x_k^q + J^s t_k^c. \tag{C.37}$$

The state space model for the controller $\bar{C}$ is,

$$x_{k+1}^{\bar{C}} = F^{\bar{C}} x_k^{\bar{C}} + \begin{pmatrix} G_{sf}^{\bar{C}} & G_{sh}^{\bar{C}} & G_{st}^{\bar{C}} \end{pmatrix} \begin{pmatrix} f_k \\ h_k' \\ t_k' \end{pmatrix}, \tag{C.38}$$

$$s_k' = H^{\bar{C}} x_k^{\bar{C}}. \tag{C.39}$$

The state space model for the controller $s_k^c = F_2^{-1} s_k'$ is,

$$x_{k+1}^c = F^h x_k^c + G^h s_k', \tag{C.40}$$

$$s_k^c = H^h x_k^c + J^h s_k'. \tag{C.41}$$

Hence the frequency weighted LQG controller for implementation can be described by the state space system,

$$\begin{pmatrix} x^p \\ x^q \\ x^{\bar{C}} \\ x^c \end{pmatrix}_{k+1} = \begin{pmatrix} F^r & 0 & 0 & 0 \\ 0 & F^s & 0 & 0 \\ G_{sh}^{\bar{C}} H^r & G_{st}^{\bar{C}} H^s & F^{\bar{C}} & 0 \\ 0 & 0 & G^h H^{\bar{C}} & \end{pmatrix} \begin{pmatrix} x^p \\ x^q \\ x^{\bar{C}} \\ x^c \end{pmatrix}_k + \begin{pmatrix} 0 & G^r & 0 \\ 0 & 0 & G^s \\ G_{sf}^{\bar{C}} & G_{sh}^{\bar{C}} J^r & G_{st}^{\bar{C}} J^s \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} f_k \\ h_k^c \\ t_k^c \end{pmatrix}, \tag{C.42}$$

$$s_k^c = \begin{pmatrix} 0 & 0 & J^h H^{\bar{C}} & H^h \end{pmatrix} \begin{pmatrix} x^p \\ x^q \\ x^{\bar{C}} \\ x^c \end{pmatrix}_k . \tag{C.43}$$

Appendix D

An Alternative Proof of Theorem 7.1

Consider the design of a frequency weighted controller, C. As explained in Section 4.2, by transforming the plant and disturbance models according to (4.6), the frequency weighted LQG controller design can be solved through standard LQG methods. Consequently, for the analysis presented in this Appendix, the designed closed loop of Figure 7.3 features the plant model, $\hat{\bar{P}} = \hat{P}$, and a frequency transformed disturbance model, $\hat{\bar{H}} = \hat{H}F$. The standard LQG controller design on $\hat{\bar{P}}, \hat{\bar{H}}$ delivers an optimal controller, $\bar{C}$, which for a SISO disturbance rejection design is the optimal frequency weighted controller, C.

Suppose that the plant model, $\hat{\bar{P}}$, can be written in state space form,

$$
\begin{aligned}
x_{k+1} &= Ax_k + Bu_k^f, && \text{(D.1)}\\
y_k^f &= Cx_k + v_k^f, && \text{(D.2)}
\end{aligned}
$$

where A, B, C are the system matrices, and v_k^f is the additive disturbance acting on the plant model output y_k^f. A similar state space representation can be derived for the disturbance model $\hat{\bar{H}}$. That is,

$$
\begin{aligned}
x_{k+1}^d &= A^d x_k^d + B^d p_k^f, && \text{(D.3)}\\
v_k^f &= C^d x_k^d + q_k^f, && \text{(D.4)}
\end{aligned}
$$

where A^d, B^d, C^d are the system matrices, p_k^f and q_k^f are respectively, the process and measurement noises associated with the disturbance model.

As described in Bitmead *et al* (1990), the state space realisation of the plant and disturbance models can be combined into a composite state space representation given by,

$$
\begin{aligned}
x^f_{k+1} &= \begin{pmatrix} A & 0 \\ 0 & A^d \end{pmatrix} x^f_k + \begin{pmatrix} B \\ 0 \end{pmatrix} u^f_k + \begin{pmatrix} 0 \\ B^d \end{pmatrix} p^f_k, && \text{(D.5)} \\
&\triangleq A^m x^f_k + B^m u^f_k + W^m p^f_k, && \text{(D.6)} \\
y^f_k &= (\, C \quad C^d \,)\, x^f_k + q^f_k, && \text{(D.7)} \\
&\triangleq C^m x^m_k + q^f_k. && \text{(D.8)}
\end{aligned}
$$

The Kalman predictor state estimator for the above composite state vector, x^f_{k+1}, may now be constructed as,

$$
\begin{aligned}
\hat{x}^f_{k+1|k} &= A^m \hat{x}^f_{k|k-1} + B^m u^f_k + M^p(y^f_k - C^m \hat{x}^f_{k|k-1}), && \text{(D.9)} \\
&= (A^m - M^P C^m)\hat{x}^f_{k|k-1} + B^m u^f_k + M^P y^f_k, && \text{(D.10)}
\end{aligned}
$$

where M^P is Kalman predictor gain.

The frequency weighted LQ criterion, (7.20), gives an LQG controller with an LQ control law of the form,

$$
\begin{aligned}
u^f_k &= -(\, L^p \quad L^d \,)\, \hat{x}^f_{k|k-1}, && \text{(D.11)} \\
&\triangleq -L^m \hat{x}^f_{k|k-1}, && \text{(D.12)}
\end{aligned}
$$

where L^p, L^d are LQ gains associated with the plant and disturbance models, and $\hat{x}^f_{k|k-1}$ is the state estimate given by the Kalman predictor (D.10).

Combining the Kalman predictor (D.10) with the LQ feedback control law (D.12) yields,

$$
\begin{aligned}
u^f_k &= -L^m(zI - A^m + B^m L^m)^{-1} M^p[y^f_k - C^m \hat{x}^f_{k|k-1}], && \text{(D.13)} \\
&= -L^m(zI - A^m + B^m L^m)^{-1} M^p \nu^{des}_k, && \text{(D.14)}
\end{aligned}
$$

where ν^{des}_k is the Kalman predictor innovations process in the designed closed loop. By definition, the innovations process, ν^{des}_k, is the error between the predicted output, $C^m \hat{x}^f_{k|k-1}$, and the measured output y^f_k, that is,

$$
\tilde{y}^f_k \triangleq -C^m \hat{x}^f_{k|k-1} + y^f_k. \tag{D.15}
$$

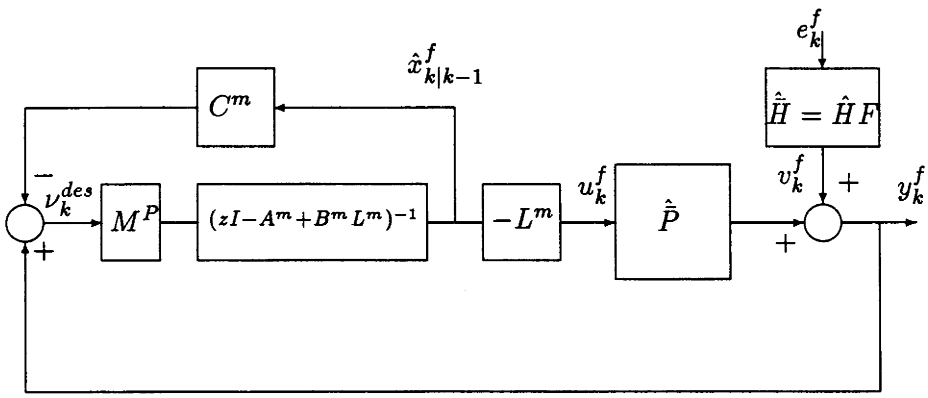

Figure D.1: The designed closed loop system for the system $(\hat{\hat{P}}, \hat{\hat{H}})$ with input-output signals, $\{y_k^f, u_k^f\}$, and the Kalman Predictor innovations, ν_k^{des}.

Figure D.1 explicitly shows the innovations process, ν_k^{des}, in the designed closed loop.

Using (D.10) and (D.12) to substitute for the estimated state vector, $\hat{x}_k^f$, in terms of the plant output, y_k^f, in the above equation (D.15), the designed closed loop innovations process ν_k^{des} becomes,

$$\nu_k^{des} = [I + C^m(zI - A^m + B^mL^m)^{-1}M^p]^{-1}y_k^f. \tag{D.16}$$

This innovations process can be expressed in terms of the white noise sequence, e_k^f, which drives the disturbance model, $\hat{\hat{H}}$, as,

$$\begin{aligned} \nu_k^{des} &= [I + C^m(zI - A^m + B^mL^m)^{-1}M^P]^{-1}[1 + \bar{C}\hat{P}]^{-1}\hat{H}Fe_k^f & \text{(D.17)} \\ &\triangleq T(z)e_k^f. & \text{(D.18)} \end{aligned}$$

As the innovations in the transformed designed closed loop system are white, the transfer function, $T(z)$, must be all-pass.

Now consider the implementation of the frequency weighted LQG controller, C, in the achieved closed loop. Using the innovations definition given in (D.15), the difference between the achieved closed loop output, y_k, and the output of the Kalman predictor associated with the controller, C, is given by the signal, ν^{ach},

$$\nu_k^{ach} = -C^m\hat{x}_{k|k-1}^f + y_k. \tag{D.19}$$

$$= \quad [I + C^m(zI - A^m + B^m L^m)^{-1} M^P]^{-1}[1 + CP]^{-1} H e_k, \tag{D.20}$$

$$= \quad T(z)\frac{[1 + \bar{C}\hat{P}]H}{[1 + CP]\hat{H}F} e_k. \tag{D.21}$$

Taking the minimum phase spectral factor, $F(e^{j\omega})$, as given by equation, (7.8), and recalling that $C = \bar{C}$, causes (D.21) to yield,

$$\tilde{y}_k = T(z)e_k. \tag{D.22}$$

Hence, providing the result of Theorem 7.1.

Appendix E

Mill Settings and Roller Diameters

This Appendix details the pressure feeder, feed nip, and delivery nip mill settings at the time controller trials were conducted on the individual mills during the 1994, 1993, 1991, crushing seasons. The diameters of the pressure feeder and milling rollers at the start of each crushing season are also displayed. Roller diameters for the 1991 crushing season were no longer available at the time of thesis preparation.

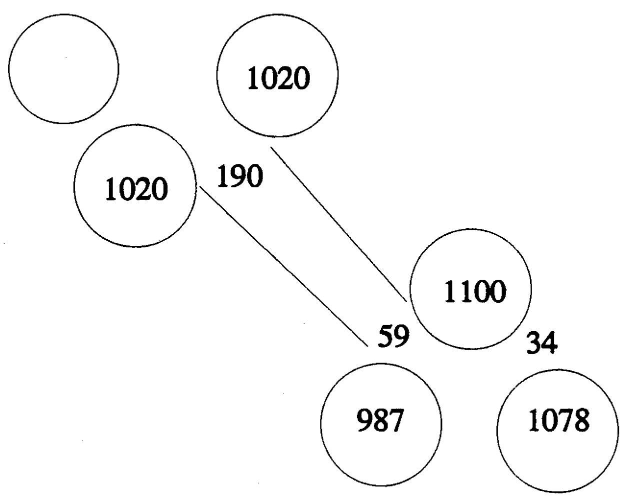

Figure E.1: A2 Mill Settings and Roller Diameters - 1994 Crushing Season.

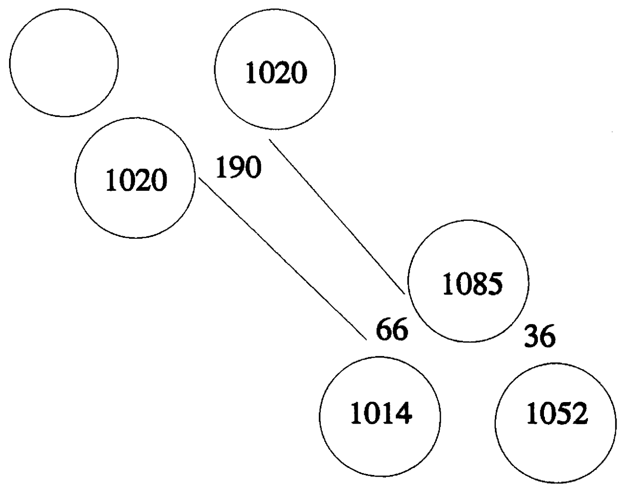

Figure E.2: A2 Mill Settings and Roller Diameters - 1993 Crushing Season.

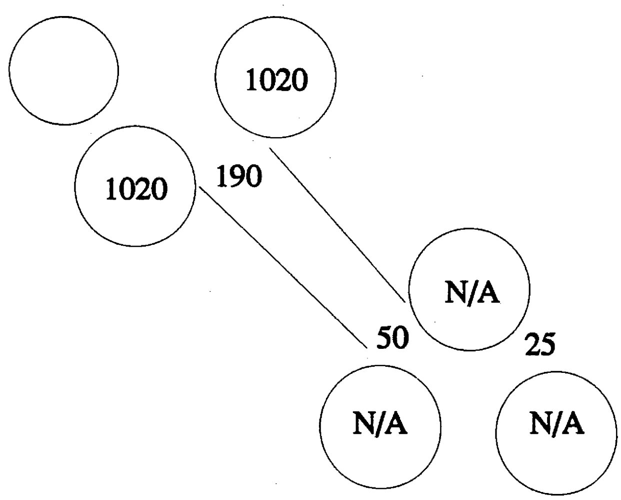

Figure E.3: A2 Mill Settings and Roller Diameters - 1991 Crushing Season.

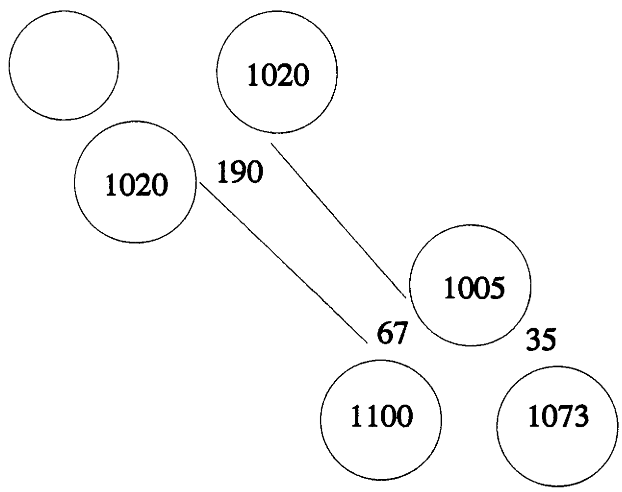

Figure E.4: A3 Mill Settings and Roller Diameters - 1994 Crushing Season.

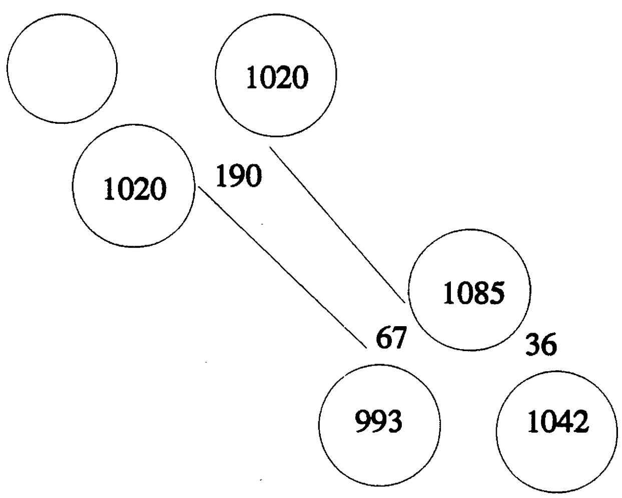

Figure E.5: A3 Mill Settings and Roller Diameters - 1993 Crushing Season.

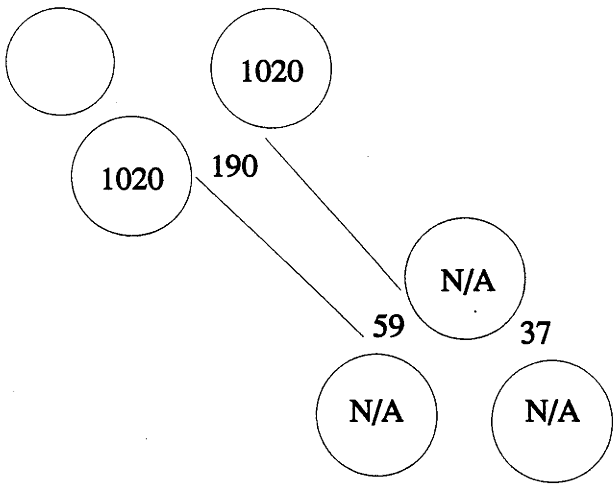

Figure E.6: A3 Mill Settings and Roller Diameters - 1991 Crushing Season.

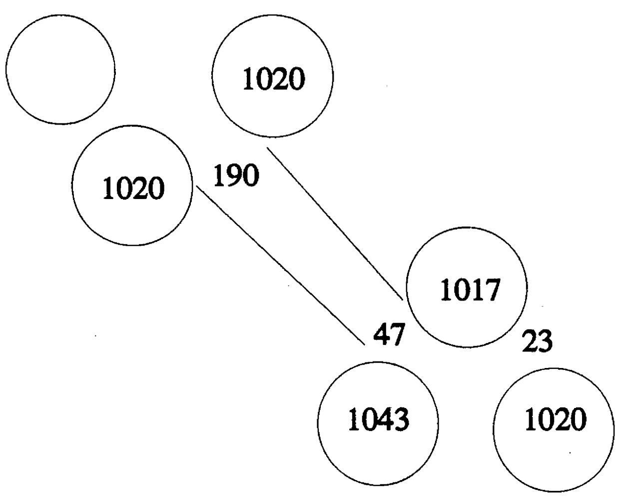

Figure E.7: A4 Mill Settings and Roller Diameters - 1994 Crushing Season.

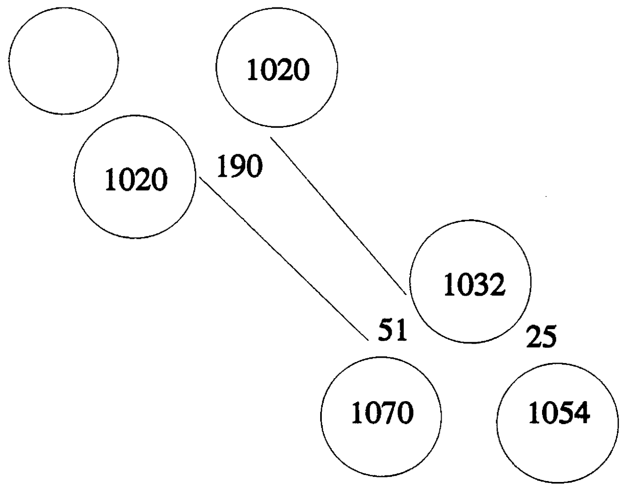

Figure E.8: A4 Mill Settings and Roller Diameters - 1993 Crushing Season.

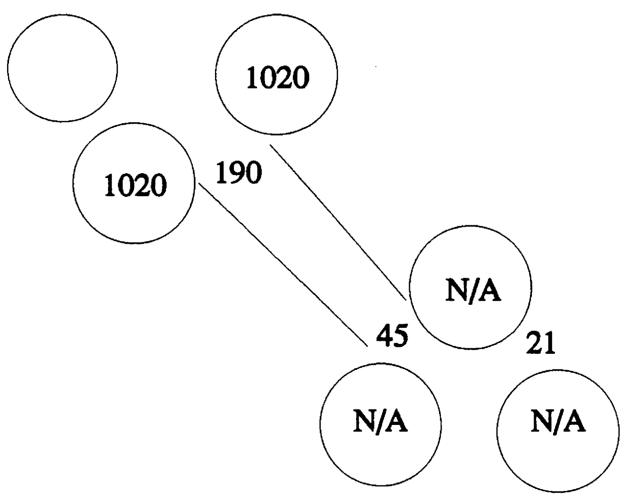

Figure E.9: A4 Mill Settings and Roller Diameters - 1991 Crushing Season.

Appendix F

LQG Controller Parameters

The controller parameters are presented in data file format which was used to implement the controller on the μVAX 2000 model-based control computer, nodename INGH08. The controller parameters together with user supplied set-points and options selections are loaded into memory by a FORTRAN program. Another FORTRAN program implements the controller difference equation. At every sample instance this program reads from memory the controller parameters, set-points, and the logic information concerning option selection, before sending the updated controller output values to the process actuators via the N90 distributed control system. The importance of fast and accurate downloading of controller parameters for successful controller development cannot be underestimated.

Although not displayed, the data file format also includes the provision for six feedforward parameters. An alternative format is also available for implementing 2i2o controllers.

A2 Mill

LQG Height Controller

```
Speed parameter number 1              =   1.9455000162
Speed parameter number 2              =  -1.3121000528
Speed parameter number 3              =   0.1678999960
Speed parameter number 4              =   0.1814000010
Speed parameter number 5              =   0.0000000000
Speed parameter number 6              =   0.0000000000
Speed from height parameter number 1 =   0.4905300000
Speed from height parameter number 2 =  -0.3705300000
Speed from height parameter number 3 =  -0.1002700000
Speed from height parameter number 4 =   0.0142700000
Speed from height parameter number 5 =   0.0000000000
Speed from height parameter number 6 =   0.0000000000
Speed from flap parameter number 1   =   0.0000000000
Speed from flap parameter number 2   =   0.0000000000
Speed from flap parameter number 3   =   0.0000000000
Speed from flap parameter number 4   =   0.0000000000
Speed from flap parameter number 5   =   0.0000000000
Speed from flap parameter number 6   =   0.0000000000
Speed from torq parameter number 1   =   0.0000000000
Speed from torq parameter number 2   =   0.0000000000
Speed from torq parameter number 3   =   0.0000000000
Speed from torq parameter number 4   =   0.0000000000
Speed from torq parameter number 5   =   0.0000000000
Speed from torq parameter number 6   =   0.0000000000
```

Direct LQG Height Controller

Speed parameter number 1	=	1.0605002323
Speed parameter number 2	=	-0.0809149826
Speed parameter number 3	=	0.0222833082
Speed parameter number 4	=	0.0473990040
Speed parameter number 5	=	-0.4363607064
Speed parameter number 6	=	0.3575275271
Speed from height parameter number 1	=	1.2338191237
Speed from height parameter number 2	=	-1.2664856440
Speed from height parameter number 3	=	0.0394854190
Speed from height parameter number 4	=	0.0391385589
Speed from height parameter number 5	=	0.0224990673
Speed from height parameter number 6	=	0.0000000000
Speed from flap parameter number 1	=	0.0000000000
Speed from flap parameter number 2	=	0.0000000000
Speed from flap parameter number 3	=	0.0000000000
Speed from flap parameter number 4	=	0.0000000000
Speed from flap parameter number 5	=	0.0000000000
Speed from flap parameter number 6	=	0.0000000000
Speed from torq parameter number 1	=	0.0000000000
Speed from torq parameter number 2	=	0.0000000000
Speed from torq parameter number 3	=	0.0000000000
Speed from torq parameter number 4	=	0.0000000000
Speed from torq parameter number 5	=	0.0000000000
Speed from torq parameter number 6	=	0.0000000000

LQG Torque Controller - C_0

```
Speed parameter number 1              =   3.4294967651
Speed parameter number 2              =  -4.4304814339
Speed parameter number 3              =   2.5967171192
Speed parameter number 4              =  -0.6267871261
Speed parameter number 5              =   0.0311435387
Speed parameter number 6              =  -0.0001856438
Speed from height parameter number 1 =   0.0846509372
Speed from height parameter number 2 =  -0.2164497277
Speed from height parameter number 3 =   0.1833723668
Speed from height parameter number 4 =  -0.0512934387
Speed from height parameter number 5 =  -0.0001805887
Speed from height parameter number 6 =   0.0000086139
Speed from flap parameter number 1   =   0.1368992092
Speed from flap parameter number 2   =  -0.3597726653
Speed from flap parameter number 3   =   0.2995574949
Speed from flap parameter number 4   =  -0.0657701494
Speed from flap parameter number 5   =  -0.0105745305
Speed from flap parameter number 6   =  -0.0003146756
Speed from torq parameter number 1   =   1.6578897461
Speed from torq parameter number 2   =  -4.5194520267
Speed from torq parameter number 3   =   4.2215928416
Speed from torq parameter number 4   =  -1.4411411793
Speed from torq parameter number 5   =   0.0865813221
Speed from torq parameter number 6   =  -0.0008951773
```

LQG Torque Controller - C_1

Speed parameter number 1	=	3.9734337330
Speed parameter number 2	=	-6.0693311691
Speed parameter number 3	=	4.2787642479
Speed parameter number 4	=	-1.1774127483
Speed parameter number 5	=	-0.0719392374
Speed parameter number 6	=	0.0664788857
Speed from height parameter number 1	=	0.1324049681
Speed from height parameter number 2	=	-0.4696018696
Speed from height parameter number 3	=	0.6367249489
Speed from height parameter number 4	=	-0.4015430808
Speed from height parameter number 5	=	0.1100500673
Speed from height parameter number 6	=	-0.0080252094
Speed from flap parameter number 1	=	0.1074845344
Speed from flap parameter number 2	=	-0.3001224697
Speed from flap parameter number 3	=	0.2137279660
Speed from flap parameter number 4	=	0.0915172398
Speed from flap parameter number 5	=	-0.1610483825
Speed from flap parameter number 6	=	0.0484420992
Speed from torq parameter number 1	=	6.6175832748
Speed from torq parameter number 2	=	-23.8650894165
Speed from torq parameter number 3	=	33.9768867493
Speed from torq parameter number 4	=	-24.4255809784
Speed from torq parameter number 5	=	9.3136243820
Speed from torq parameter number 6	=	-1.6170933247

LQG Torque Controller - C_2

```
Speed parameter number 1                =   4.9439554214
Speed parameter number 2                = -10.3202419281
Speed parameter number 3                =  11.6324110031
Speed parameter number 4                =  -7.4564018250
Speed parameter number 5                =   2.5718538761
Speed parameter number 6                =  -0.3716388643
Speed from height parameter number 1 =   0.2927597085
Speed from height parameter number 2 =  -1.2559189706
Speed from height parameter number 3 =   2.2062332544
Speed from height parameter number 4 =  -1.9860845414
Speed from height parameter number 5 =   0.9171421350
Speed from height parameter number 6 =  -0.1740458260
Speed from flap parameter number 1   =  -0.0415232048
Speed from flap parameter number 2   =   0.2322801860
Speed from flap parameter number 3   =  -0.5129943635
Speed from flap parameter number 4   =   0.5659658096
Speed from flap parameter number 5   =  -0.3143580072
Speed from flap parameter number 6   =   0.0706317971
Speed from torq parameter number 1   =   9.5360427003
Speed from torq parameter number 2   = -39.1365770774
Speed from torq parameter number 3   =  65.0345302854
Speed from torq parameter number 4   = -54.6290730794
Speed from torq parameter number 5   =  23.1379011257
Speed from torq parameter number 6   =  -3.9396024700
```

A3 Mill

LQG Torque Controller - C_0

Speed parameter number 1	=	4.9439554214
Speed parameter number 2	=	-10.3202419281
Speed parameter number 3	=	11.6324110031
Speed parameter number 4	=	-7.4564018250
Speed parameter number 5	=	2.5718538761
Speed parameter number 6	=	-0.3716388643
Speed from height parameter number 1	=	0.2927597085
Speed from height parameter number 2	=	-1.2559189706
Speed from height parameter number 3	=	2.2062332544
Speed from height parameter number 4	=	-1.9860845414
Speed from height parameter number 5	=	0.9171421350
Speed from height parameter number 6	=	-0.1740458260
Speed from flap parameter number 1	=	-0.0415232048
Speed from flap parameter number 2	=	0.2322801860
Speed from flap parameter number 3	=	-0.5129943635
Speed from flap parameter number 4	=	0.5659658096
Speed from flap parameter number 5	=	-0.3143580072
Speed from flap parameter number 6	=	0.0706317971
Speed from torq parameter number 1	=	9.5360427003
Speed from torq parameter number 2	=	-39.1365770774
Speed from torq parameter number 3	=	65.0345302854
Speed from torq parameter number 4	=	-54.6290730794
Speed from torq parameter number 5	=	23.1379011257
Speed from torq parameter number 6	=	-3.9396024700

LQG Torque Controller - C_1

```
Speed parameter number 1                 =    4.7362396748
Speed parameter number 2                 =   -9.4547562774
Speed parameter number 3                 =   10.2255297422
Speed parameter number 4                 =   -6.3573176826
Speed parameter number 5                 =    2.1723733589
Speed parameter number 6                 =   -0.3221617531
Speed from height parameter number 1 =    0.1658473240
Speed from height parameter number 2 =   -0.6524666514
Speed from height parameter number 3 =    1.0331508039
Speed from height parameter number 4 =   -0.8223023571
Speed from height parameter number 5 =    0.3281199946
Speed from height parameter number 6 =   -0.0522640866
Speed from flap parameter number 1   =   -0.0415232033
Speed from flap parameter number 2   =    0.2322801799
Speed from flap parameter number 3   =   -0.5129943490
Speed from flap parameter number 4   =    0.5659658313
Speed from flap parameter number 5   =   -0.3143579960
Speed from flap parameter number 6   =    0.0706317946
Speed from torq parameter number 1   =    9.4676117163
Speed from torq parameter number 2   =  -37.5669075184
Speed from torq parameter number 3   =   60.2020427023
Speed from torq parameter number 4   =  -48.7240488957
Speed from torq parameter number 5   =   19.9072299987
Speed from torq parameter number 6   =   -3.2811582714
```

A4 Mill

LQG Torque Controller - C_0

```
Speed parameter number 1               =   4.9439554214
Speed parameter number 2               = -10.3202419281
Speed parameter number 3               =  11.6324110031
Speed parameter number 4               =  -7.4564018250
Speed parameter number 5               =   2.5718538761
Speed parameter number 6               =  -0.3716388643
Speed from height parameter number 1 =   0.2927597085
Speed from height parameter number 2 =  -1.2559189706
Speed from height parameter number 3 =   2.2062332544
Speed from height parameter number 4 =  -1.9860845414
Speed from height parameter number 5 =   0.9171421350
Speed from height parameter number 6 =  -0.1740458260
Speed from flap parameter number 1   =  -0.0415232048
Speed from flap parameter number 2   =   0.2322801860
Speed from flap parameter number 3   =  -0.5129943635
Speed from flap parameter number 4   =   0.5659658096
Speed from flap parameter number 5   =  -0.3143580072
Speed from flap parameter number 6   =   0.0706317971
Speed from torq parameter number 1   =   9.5360427003
Speed from torq parameter number 2   = -39.1365770774
Speed from torq parameter number 3   =  65.0345302854
Speed from torq parameter number 4   = -54.6290730794
Speed from torq parameter number 5   =  23.1379011257
Speed from torq parameter number 6   =  -3.9396024700
```

Appendix G

PID Controller Gains

This Appendix records the height and torque PID controller gains during the 1994, 1993, and 1991 crushing seasons. The particular PID controller gains are :-

- K the overall scaling from controller input to controller output.
- K_p is the proportional gain.
- K_i is the integral gain in repeats/minute.
- K_d is the derivative gain in minutes.

A2 Mill

Crushing Season	PID Controller							
	Height				Torque			
	K	K_p	K_i	K_d	K	K_p	K_i	K_d
1994	1.0	2.0	2.0	0.1	66.7	1.5	2.5	0.1
1993	1.0	3.0	2.0	0.1	66.7	1.0	1.5	0.6
1991	1.0	3.0	2.0	0.1	66.7	1.0	1.5	0.6

Table G.1: A2 Mill Height and Torque PID Controller Gains.

A3 Mill

Crushing Season	PID Controller							
	Height				Torque			
	K	K_p	K_i	K_d	K	K_p	K_i	K_d
1994	1.0	1.4	0.9	0.0	66.7	2.0	1.0	0.0
1993	1.0	1.6	0.85	0.0	66.7	2.0	1.0	0.0
1991	1.0	1.2	0.85	0.0	66.7	2.0	1.0	0.2

Table G.2: A3 Mill Height and Torque PID Controller Gains.

A4 Mill

Crushing Season	PID Controller							
	Height				Torque			
	K	K_p	K_i	K_d	K	K_p	K_i	K_d
1994	1.0	1.2	1.7	0.125	66.7	1.2	2.0	1.0
1993	1.0	1.2	1.7	0.125	66.7	1.2	2.0	1.0
1991	1.0	1.2	1.7	0.0	66.7	1.2	2.0	1.0

Table G.3: A4 Mill Height and Torque PID Controller Gains.

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[1]Vowels, å,ä,ö, which are not part of the english language appear at the end of the alphabet, as is the case with the languages in which some or all of these vowels feature, e.g Finnish, Swedish.

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